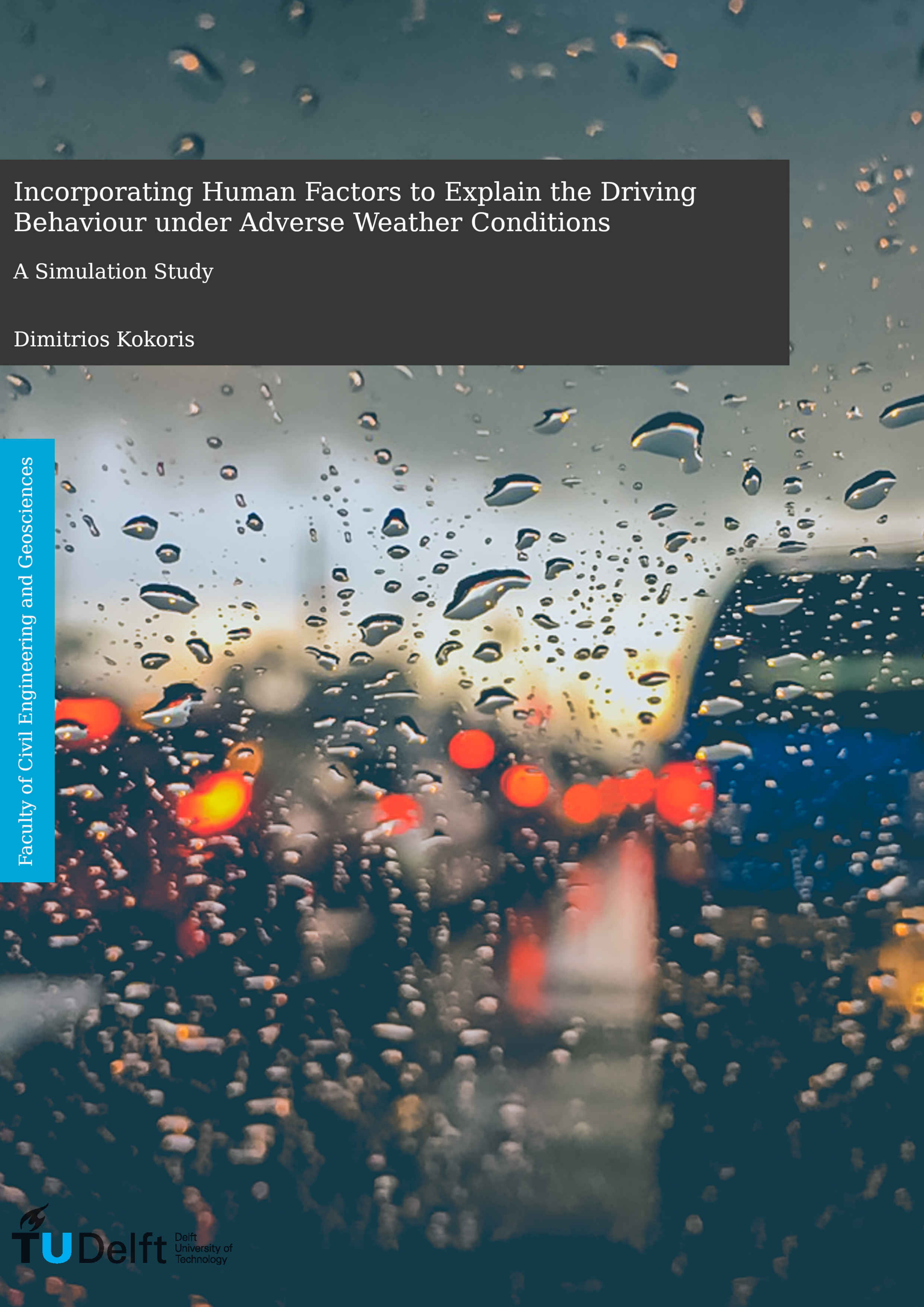

Incorporating Human Factors to Explain the Driving Behaviour under Adverse Weather Conditions

A Simulation Study

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Incorporating Human Factors to Explain the Diving Behaviour under Adverse Weather Conditions
A Simulation Study

Master of Science in Civil Engineering and Geosciences
Track Transport and Planning

by

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September 2021

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Dimitrios A Kokoris: *Incorporating Human Factors to Explain the Diving Behaviour under Adverse Weather Conditions A Simulation Study* (2021)

 The picture illustrated in the cover photo stems from https://www.seattlemag.com/city-life/art-driving-seattle-rain, City Life, The Art of Driving in the Seattle Rain, November 2018.

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I

Science is a way of thinking much more than it is a body of knowledge. Its goal is to find out how the world works, to seek what regularities there may be, to penetrate the connections of things—from subnuclear particles, which may be the constituents of all matter, to living organisms, the human social community, and thence to the cosmos as a whole. Our intuition is by no means an infallible guide. Our perceptions may be distorted by training and prejudice or merely because of the limitations of our sense organs, which, of course, perceive directly but a small fraction of the phenomena of the world. Even so straightforward a question as whether in the absence of friction a pound of lead falls faster than a gram of fluff was answered incorrectly by Aristotle and almost everyone else before the time of Galileo. Science is based on experiment, on a willingness to challenge old dogma, on an openness to see the universe as it really is. Accordingly, science sometimes requires courage—at the very least the courage to question the conventional wisdom.

Carl Sagan

ACKNOWLEDGEMENTS

This thesis would not have been completed without the moral, ethical, psychological and passive or active contributions of several people.

First, I would like to thank my daily supervisor Simeon Calvert for the guidance, advice and constructive feedback that you provided me along all stages of the thesis. Thank you Simeon for all your inspiration, knowledge and friendly research environment. I would like to thank Professor Hans van Lint, Wouter Schakel and Yilin Huang for all advise, constructive feedback, and the eagled-eyes on detail that you provided me to improve my scientific approach.

Second, people in this life really matter. Especially, good friends. A gargantuan thank to my Deft-mates Panos, Roxani, Pantelis and Alexandra for your support and patience of a man who deals with the world stoically. Alex, thanks for your support and love. Special thanks and cheers to Vasilina, Anastasia, Panagiotis, Shubham, Sourabh, Sena, Paula, Vini, David, Nikiforos for the moments we have been through. Special thanks to my 'amico' Stathis, Giannis, Vaggelis and Nikos for all the support and genuine friendship since we met.

Finally, I would like to thank true heroes, my family!

All these contributed to a great TU Delft experience.

Dimitris Kokoris
Delft, September 2021

EXECUTIVE SUMMARY

Modern societies have heavily relied on efficient transportation systems for mobilizing people and goods. These propelling systems are constituted by road traffic networks. Currently, traffic demand is so high and perpetually increasing with unprecedented rates that traffic congestion has become an imminent subsequent. Over time, all this human activity that has established the status-quo of modern societies has negatively contributed to climate change. The climate deviations are prominent in urban environments with a higher frequency of events and elongated time scales. Therefore, road traffic systems jeopardizing their robustness and resilience is at stake. A fundamental component in road traffic systems plays a human factor. Nevertheless, the human factors, to the contribution in traffic, is neglected most of the time. Some other times we consider that humans act rationally. Consequently, engineers seek answers to burning questions of how to incorporate the human factor into the system to explain the behaviour of human drivers under such particular conditions.

In an attempt to approach the subject, the most appropriate level of analysis is the microscopic level. At this level, vehicles are modelled as discrete agents governed by ordinary differential equations expressing the rate of change in velocity over continuous (or discrete) time. In the literature, the vast majority of the proposed mathematical formulations revolve around the physics of the subject enclosing only physical parameters that are observable. Might be the only parameter that in some studies attributed as the human factor is the reaction time. In reality, this commutative property transforms the ordinary differential equation into a delayed ordinary differential equation with known traffic instabilities. There is a strand in the literature that addresses models with human factor parameters such as the Wiedeman model giving room for investigation. In recent years, we have admitted studies that rely on psychology science in an attempt to enrich the solid mathematical models with explanatory knowledge. This dire need has already been addressed by studies such as (Saifuzzaman & Zheng, 2014) . Adverse weather conditions is deemed an external disturbance to the vehicular traffic must be seen as a factor that influences both the physics of the vehicle and the humans. To investigate the subject, approaches like collecting data and calibrating a given Newtonian-like equation is obsolete. This descriptive knowledge is changing into explanatory if we reasonably include mental constructs influenced by psychology and cognitive engineering. This direction of research has been pointed out in the studies of (Saifuzzaman, Zheng, Haque, & Washington, 2015), (Van Lint & Calvert, 2018) . The pivotal point of the recent studies compared to the previous in the past is the explanatory knowledge that contains. Studies in the previous years mainly approach the matter out of mathematical curiosity. That said, we spot a breeding ground to grow this research by considering that the adverse weather conditions influence human factors and this, in turn, can offer a valid explanation to phenomena we observe in the aggregate traffic.

The two main human factor processes are perception and response. The perception process is highly connected with the mental model of Endsleys Situation Awareness. SA regards the perception of the stimuli of the environment, the comprehension of their meaning and the projection in a future state. The response process is connected with Fuller's TCI mental model. TCI regards the difference between task demands and the capability of the driver. This difference is translated as a subjective risk of a given task. When the risk is high, drivers are motivated to change their behaviour. This behavioural adaptation is a key concept to safe driving. The parameters of speed and time headway are considered that the drivers can deviate for the sake of safe driving. Below, we give the conceptual framework of driving in rain as well as a brief explanation of the various components. (Van Lint & Calvert, 2018) proposed a multilevel framework that explicitly includes parameters of human factor cognitive processes on which an extension of this framework is developed further in this thesis to account for the adverse weather conditions. At the highest level of the framework, we admit a car-following model that, in principle is collision-free. At the lower level, state variables are defined that controls how many tasks the drivers execute and what is the impact of human information processing on perception and response. These two levels are connected with the function that governs the dynamics of the human parameter. The disturbance of adverse weather conditions exerts an impact on elements of the framework that, consequently, influence vehicle kinematics and the drivers psycho-cognition. Initially, (b) total task demand is computed for each related to driving task by the so-called fundamental diagrams of task demand (FDTD) (a). Thereafter, the output of this demand is

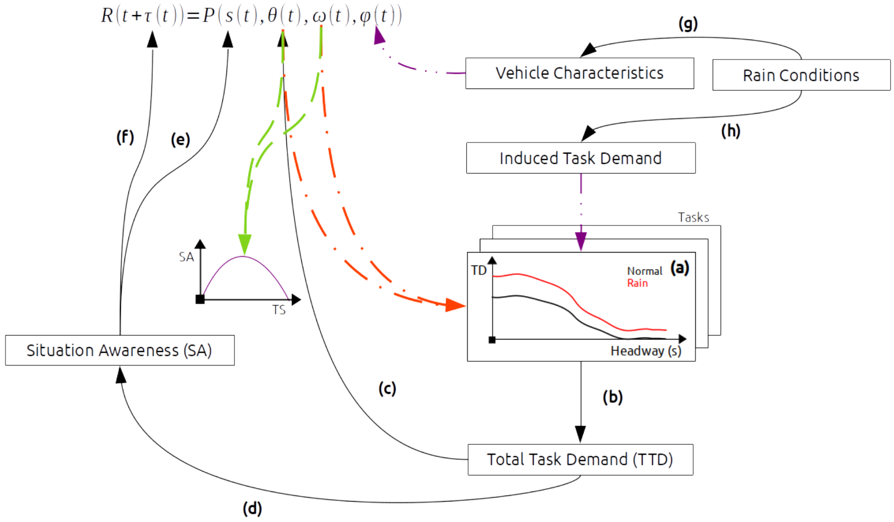


Figure 0.1: Proposed conceptual framework under rainy conditions

computed on (c) driver characteristics which concern behavioural adaptation and on (d) SA. Depending on the state of SA, is then computed the influence on (f) perception errors and (e) reaction times. With the disturbance of rain, the (g) agility of the vehicle is affected and the hypothesized (h) induced task demand on the existing driving task(s) is in effect.

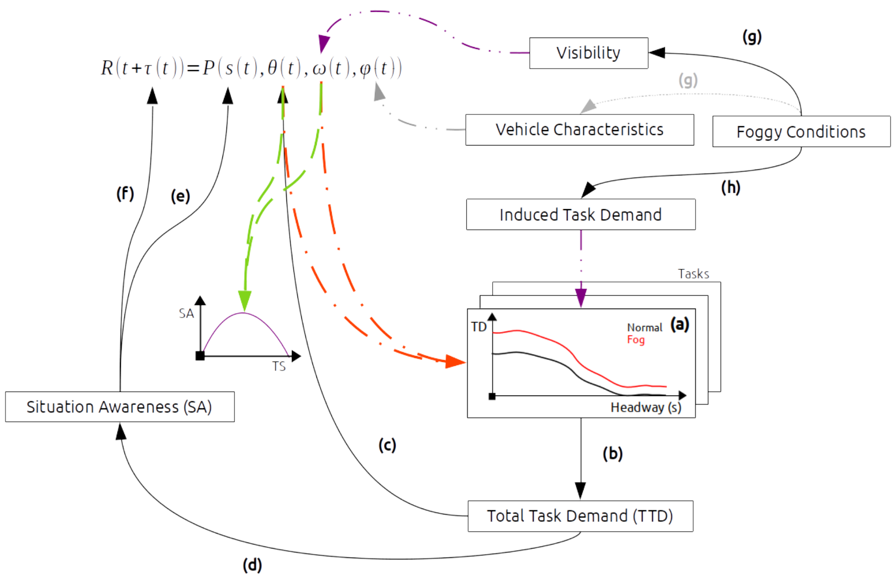


Figure 0.2: Proposed conceptual framework under rainy conditions

Similarly, we frame the conceptual framework when driving under foggy conditions. The final derivative is illustrated in figure 0.2. The basic structure of this framework is the same as the one of (Van Lint & Calvert, 2018) enriched with the knowledge of the recent study. Foggy conditions exert impact on (g) visual acuity of drivers' and, therefore, their perceivable world is distorted due to the physiological sensors (eyes) degradation. The distance distortion of the perceivable world is known to governed by a power-law form, while for the speed perception is not known yet the distortion if any.

The extensions of conceptual frameworks that we developed here are evaluated with an exploratory simulation case study. The study concerns a one-directional roadway with a length of 6km and a maximum speed of 120km/h. In the present study, we considered only one class of vehicles. The traffic flow demand profile is also hypothetical, while reflects high-intensity conditions, with peak demand at 2200veh/h. To allow interactions between the vehicles we set an artificial bottleneck at a distance of 4km for 250 meters. We set the bottleneck in the simulation is by varying the time headway of the vehicles to a constant value. That makes the bottleneck flow conserving. Regarding the stochasticity of the simulations we run each scenario only once. This fact raise some further concerns regarding the validity of the produced results.

The exploratory simulation study shows that the inclusion of human factors with novel approaches, such as Fuller's Task-Capability-Interface and Endsley's Situation awareness, has the of explaining and generating the driving behaviour of the traffic stream. Judging the simulation results from the perspective of the fundamental diagrams of traffic flow we can argue that the results do not contain any irregular behaviour concerning the applied theory. That holds in the most of the assessed cases. Accordingly, the majority of the generated traffic patterns do not include any behaviour that the traffic flow cannot explain. Nevertheless, we admitted some traffic patterns that does not hold good. Regarding the state - variables that are included, the trace figures shows that the interactions between the psycho-cognitive mechanisms are influenced by each other as they planned. In addition, the impact that these psycho-cognitive mechanisms exert on the collision-free model is such to produce reasonable responses. More specifically, from the perspective of the performance measure of TTS, we do not admit very high and not explainable responses of the model. In the literature, we find that the speed reduction of empirical cases follow the same trend as we produced in our simulations when this information are available. Notably, some artefacts are seen in the simulations such as when the mechanism of overestimation of distances is in effect for the case of rain. In which case, we admitted many collisions of chain-like fashion that are not likely to occur under real conditions. The insightful result we obtain when all the mechanisms are in effect and additionally we set heterogeneity of the driving population is that the bottleneck is pinched locally without propagating to the upstream.

In the present study, many implementations of the framework are subjected to many assumptions. Many of them are speculative at best. First, the behavioural adaptation of drivers (desired speed and/or time headway) as a response to high task saturation may be considered as one. Nevertheless, this assumption has a solid theoretical basis on Fuller's work of allostasis theory. There is ample empirical evidence that drivers adapt their behaviour in rainy and foggy conditions, while desired speed seems to be the predominant relief action to follow. In addition, one can argue that the desired speed and time headway are parameters that manifest in the mathematical formalisation depending on the longitudinal model that someone uses. Second, we assume that adverse weather conditions influences drivers' cognition. We propose the concept of the so-called induced task demand due to the weather, and the driving task becomes more demanding under such conditions. To operationalize its meaning we further assume that a strong indicator of task demand resides in the preferred time headway parameter. Someone can interpret it as an inverse engineering approach. On one hand, there is some theoretical evidence of this in the works of , on the other hand, no empirical evidence we are able to trace until this now. Since we have no clue about this relationship, we further assume that the parameters have a proportional interaction. Inevitably, this is open for further discussion whether such a linear relationship exists. Third, by following Endlsley's situation awareness, we further assume that the degradation of the SA performance potentially deteriorates the perceptual biases and reaction time. In the literature, under different condition-specific circumstances, there exist different perceptual biases. Some of them are well addressed in this study, while some other are still unknown and, thus, further research is needed. Fourth, we do not address the role of anticipation in the model. As suggested by Rosen (Rosen, 2012), anticipatory systems contain a predictive model of itself and/or of its environment, which allows it to change its state in an instant relying on predictions that are ascribed to a future state. It is well known from studies such as (Treiber, Kesting, & Helbing, 2006) that temporal and/or spatial anticipation, two modalities that are operationalised in traffic science to account for anticipation, have a stabilizing influence on the system for the net increase of reaction time and perceptual inaccuracies.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

Driving activity is more than a vehicle traversing a route between points A to B. Behind every steering wheel is the most complete ”system” that humans run into for decades to come, a human being. We humans attain the most efficient sensory, processing and decision making machine into the most ancient architecture, the human cerebral cortex. Interacting with the environment, interpreting the inbound signal into meaningful information and deploying a decision-making algorithm, we effectively interact with any given environment by regulating mechanical components of a car to achieve our desired goal. When it comes to capturing these human-sided processes into mathematical models, research facing a shortcoming. These highlighted processes and the accompanying assumed parameters that define them are impossible to observe in real life. With the flow of technological advancements, the position of the human driver and the influence that they have on the system of vehicle-road is still unexplored in many aspects. Amongst these aspects is the impact of adverse weather conditions on the behaviour of the human driver and the imminent influence on efficiency and safety.

Road traffic systems are highly utilized globally for various trip purposes and from different types of vehicles. In Europe, for instance, the utilization of the road system in relation to passenger vehicles-kilometres reaches 81.3% among the means of passenger transport, (Diemer & Dittrich, 2019). Such a high utilization can cause to the road traffic system impedances such as congestion, higher risk-taking with a potential incident outcome and increased emissions due to the sub-performing network. Human drivers attain the most important role into the system.

For all these reasons, human factor must be included to mathematical models. Therefore, these mathematical models must be included to simulation for further investigation. This method entails developing models that not only describe the dynamic movement of the vehicles (car-following, lane changing) but also include mathematical formulation describing the behavioural dynamics of the humans as they interact with new technologies, roadway entities, and environmental changes. By this extension, it is envisaged that the understanding of incorporating new technologies will be amplified and some of the remaining observed phenomena of the capacity drop, hysteresis and traffic oscillations which puzzle researchers and practitioners will be explained,(Saifuzzaman, Zheng, Haque, & Washington, 2017). To that end, this transition is happening the last decades as the vehicle automation seems to become a reality and the need for even more sophisticated human factors(HF) models is increasing, (Van Lint & Calvert, 2018). In the review of (Treiber & Kesting, 2013b), the human driving characteristics are defined as the followings; Finite reaction time, estimation errors, temporal and spatial anticipation, more input signals, context-sensitivity, finite perception threshold, courtesy and cooperation.
In the present research proposal, special attention will be given to the development of a model that includes HF that is critical under the disturbance of adverse weather conditions that lead to traffic flow decay. It is well known and addressed in the literature that in the presence of adverse weather conditions and slick pavement the 21% of vehicle crashes, the 19% of crash injuries and the 16% of crash fatalities is attributed, as the Federal Highway Administration shows, (FHWA, 2020). These statistics cover a span of 10 years, from 2007 to 2016. Various studies have been conducted which try to implement adverse weather conditions in simulation environments to assess the severity of the weather. Some of the studies try to explain with data-driven approaches the effects on demand and supply while some others try to incorporate the effects of the inclement weather directly to the core of the car following models in a simulation model,((Hranac et al., 2006), (van Stralen, Calvert, & Molin, 2015),(Mahmassani et al., 2009), (Snelder & Calvert, 2016a), (Hammit, James, Ahmed, & Young, 2019)). The direction of the current simulation study is to expand the collision-free logic of a microscopic model by following the conceptual model of (Van Lint & Calvert, 2018) wherein basic mental constructs are mapped. Within these mental constructs, Human Factors offer a possible explanation of the driving behaviour under adverse weather conditions.

1.1 PROBLEM DESCRIPTION

It is essential to apply effective strategies to improve or sustain at an acceptable level(defined by the policy-makers) the traffic flow and in parallel decrease the probability of collision. Nevertheless, before applying interventions to mobility, appropriate ex-ante studies need to be conducted to get a better understanding of the causes that disturb the traffic flow. A suitable experiment is needed to test all the above-mentioned. According to (Verschuren, Doorewaard, & Mellion, 2010) the experimentation is divided into three categories; Laboratory experiment, Quasi-experiments and the Imitation. In the present study, the later technique will be used. A form of imitation is the *computer simulation*. It is deemed as one of the most appropriate techniques for the following reasons; In a controlled, though the realistic environment, methodologies and new technologies can be tested and evaluated. Identify the role of the human factor in combination with the newly introduced technologies. Which in the present study this is the endeavour. They are substantially inexpensive compared to the methodologies such as field experiments or naturalistic studies. However, the computational burden is a matter of concern when using simulations.

It is commonly known that the absence of the internal human process of thinking to the mathematical models which describe the movement of the traffic it is and always has been at the core of the traffic flow modelling, (Van Lint & Calvert, 2018). These days, if someone wants to emulate a disturbance (the adverse weather conditions or any other disturbance) into a microscopic model, rationally will opt for calibration techniques to tweak the parameters of a given car following model in line with a defined objective. Even then, the calibration of the model is realised following optimization methods such as evolutionary or simulated annealing algorithms which are very tedious processes. The outcome of this process may imitate the studied phenomenon but does not contain any explanatory power. The main concern of the researchers and the practitioners, is to benefit from the psychology science by using mental constructs and address to them driving processes such as that of *perception* and *response* in combination with a car following dynamics, to describe how a disturbance has a given result and to some point *why?*. Therefore, the present research aims at contributing towards the connection between traffic flow and psychology perspective when a disturbance of the weather is present. The potential benefits by reasonably incorporating human factors that offer explanatory power to the models are discussed in the following point:

- Transition from descriptive to explanatory knowledge of disaggregate and collective behaviour
- Track and tracing individual behaviour for the purpose to spot weak points of design on the system human-vehicle-road.
- Development of micro-simulation models that allows such understanding of the system offering also reliable predictive capabilities.
- Explanation of puzzling phenomena such as capacity-drop, hysteresis e.t.c. beyond the conceptual mathematical formalization.
- As an extension given, valid and pragmatic evaluation of ITS and automated vehicles and their impacts on efficiency, safety and the environment impact.

1.2 RESEARCH GAP

The effects of severe weather on the traffic flow is a topic which concerns practitioners, researchers and road authorities worldwide. The first step towards gaining an understanding of weather phenomena is to collect field data of traffic and then describe its impacts at an aggregate level(flow, speed and density). Such studies as it is seen here((Hranac et al., 2006),(Maze, Agarwal, & Burchett, 2006),(Snelder & Calvert, 2016b)), reveals that the effects of severe weather are no negligible. Of course, the severity of each weather phenomenon can impact differently the flow(speeds) from location to location. For this reason, methodologies wanted from road authorities to tackle various weather events while the practitioners and the researchers try to understand what is the benefit of using new technologies. In studies like (Mahmassani et al., 2009), weather and traffic data were

collected and then categorized according to the severity of the weather phenomenon. The proposed methodology starts with the calibration of a mesoscopic model and a modification of the demand side with the so-called weather adaptation factors which is a regression analysis combining the visibility, the intensity of snow and rain into one model. Therefore, several weather scenarios and one benchmark scenario are defined and then, via a predictive scheme apply either strategy of VMS or rerouting(advisory of enforced). However, due to the nature of the method, the authors assume that the drivers' responsiveness to the sings would be 50%. This assumption can affect substantially the results of the model and therefore the conclusions of each intervention. This described assumption encloses in one number, the *heterogeneity* of the drivers and to some extent their *preferences* and *"capabilities"*. To expand further, similar studies at a microscopic level can be found at (Hranac et al., 2006) and (Rakha, Zohdy, Park, Krechmer, & Systematics, 2010). For instance, in the study of (Hammit et al., 2019) the so-called psycho-spacing W99 model of the VISSIM software was calibrated for the needs of that study. The simulation results were able to emulate the effects of different inclement weather but as the authors stated, due to the complex human behaviour, it is very difficult to interpret and summarize it in a single metric.
What we know today, is how to incorporate *exogenously* HF processes by applying either deterministic or stochastic values to reaction time or stimuli(gaps, speed differences) into the core of the model. A recent advancement towards applying HF to the core of the model is by using the so-called Task Difficulty process as seen in (Saifuzzaman et al., 2015) which is in the line of the Task Capability Interface (TCI) of (Fuller, 2005). By following the same approach, the authors attempt to explain the traffic hysteresis and oscillations by utilizing the proposed construct, (Saifuzzaman et al., 2017). Another evidence of the inadequacy of the psycho-spacing models and especially in the case of fog is emphasized in the study of (R. G. Hoogendoorn, Hoogendoorn, Brookhuis, & Daamen, 2011). What is proposed recently in the literature (Van Lint & Calvert, 2018), is to incorporate a human thinking process by using the (TCI) (Fuller, 2005) by directly deriving the Task Demand of a given Task, connecting it with the theory of situation awareness (Endsley, 1995) and see the outcome to the car following behaviour.

1.3 RESEARCH OBJECTIVE

The objective of the research proposal is to generate and explain the driving behaviour under the adverse weather conditions of fog and rain via simulation.

1.4 RESEARCH QUESTIONS

The main research question is formed as follows:

What are the effects of adverse weather conditions on the system vehicle and human drivers when executing the tasks of car-following, and how well can mental constructs represent this behaviour when embedded in the core of a simulation logic?

Apart from the main research question, the following subsidiary research questions are introduced to helps us answering the main research question.

1. Which are the weather phenomena that cause a disturbance to the normal traffic conditions?
   a) Which are the phenomena that affecting the normal traffic conditions and how they emerge to an aggregate level?
   b) To what extent these phenomena affects the traffic supply?
   c) What are the weather phenomena which can be incorporated into a simulation?
   d) How the inclement weather affects human behaviour?

   The first sub-question of the research demands the comprehension of the weather conditions and "how much" can affect the demand and supply side of the road network performance. Is very important to point out quantitatively the reduction of the supply side, in terms of speed, flow and capacity. This to be done by a proper literature review. After gaining an understanding of what the severe weather conditions can cause the traffic flow, the level of modelling detail must be studied.

2. What is the proper level of traffic modelling to incorporate mental constructs of human behaviour?
   a) What is the most appropriate modeling framework to be exploited in this study?
   b) What mental constructs are to exploited in the study?
   c) What parameters define the state of a human driver?
   d) How these human factors can be modelled mathematically in a simulation experiment?
   e) How the weather conditions can be reasonably incorporated into such a framework?

The second sub-question has to do with the decisions about the level-of-detail of modelling and the methodology which has to be followed to emulate the inclement weather conditions. The first decision is very important as it will define the development of the study. It is clear from the structure of the report and the related references, that the level of detail would be microscopic. At this level, the detailed representation of the traffic is accentuated while the methodology which is tailor-made for this study is developed at this level of detail. The framework that the authors (Van Lint & Calvert, 2018) propose it appears reasonable to exploit in this study. Generally, it is evident from the literature and the practice that the weather(severe) affects the tasks of driving(longitudinal and lateral) as the perception of the drivers deteriorates because of the reduced visibility in the most of the times. When a driver suffering from this temporal impairment, they either underestimate or overestimate the stimuli that are the *perceived* gap(following an ego vehicle) and the speed differences. What is more, the time to understand and then react to the stimuli increases(physical time)? Maybe the most important question here to be answered in this part is how the various weather conditions can be incorporated into the model. The followed logic says that the adverse weather conditions will create an **induced task demand (ITD))** to execute the tasks of car-following and lane changing. It is obvious that this ITD cannot be measured directly as there as so many stochastic parameters from both the side of the driver and the dynamics of the vehicles. The way to tackle this problem it could be to derive a mathematical model that contains the parameters of visibility of the driver, intensity of the weather event, and time headway. To gain more insights, the following question is proposed that contains the scenarios to be tested in the simulation study.

3. What is the performance of the modelling framework?
   a) What indicators can be used to assess the aforementioned dimensions of performance?
   b) How reasonable are the modelling responses of the framework when incorporating the case of fog.
   c) How reasonable are the modelling responses of the framework when incorporating the case of rain.
   d) Which methods of operational validation are applicable in this study?

The third phase which is an extension of the second phase is the assessment of the results. The most probable indicators that are going to used is the travel time spent for assessing the performance of the simulation from the efficiency perspective; from the safety perspective, the time to collision it seems to be a reasonable performance measure. What can be done in the study additionally, is to face-validate the performance of the simulation results by constructing the space headway(of time headway) distribution and compare it with real data of traffic. Also, some individual trajectories can be isolated and studied in depth in the case of an accident or close call to understand *how* they perform this downgraded performance.

1.5 SCIENTIFIC CONTRIBUTION

- This proposed research aims at enriching the understanding between human behaviour and vehicle dynamics under a disturbance which is the adverse weather. Dealing with a disturbance such that from a different perspective, we are capable of explaining what are the human factors responsible for the sub-performing driving behaviour.
- It is possible to include the drivers' heterogeneity(risk-taking propensity) and capabilities(novice and highly skilled drivers).

- Due to the generic nature of the framework, we can extend it towards the inclusion, at a rudimentary level, of promising ITS and ex-ante assess its impacts on the human behaviour and the traffic subsequently. This assessment is necessary as the automated vehicles seem to gain ground in the market and valid simulation framework is of dire need.
- Lastly, the simulation software itself is crucial as the current market software are rather restricted to their capabilities. It is impossible to apply the before-mentioned schemes to closed-source software and thus the open-source software is in favour.

1.6 PRACTICAL CONTRIBUTION

- Make the car-following models(lane-changing) more realistic giving more intuitive results.
- Offer possibilities of in terms of human behaviour aspects why an accident happened or it was very near to happen.
- The practitioners may be benefited from this new modelling technique logic delivering more reliable and pragmatic simulations when assessing, evaluating or proposing mitigation schemes, especially those in adverse weather conditions.

1.7 LIMITATIONS

The substantial difficulty that the incorporation of human factors introduces is the collection of traffic data[1] that are representative. To expand further, in an ideal situation that we have the data set we need, it is difficult to extract any measurement for the human factor because these factors cannot be measured. Another limitation here is the quantification of the task demand of driving behaviour. The psychological science offers a great source of which behavioural factors are connected and why, but it cannot provide both close form relationships in mathematical terms and empirical observations. As it is stressed above, the framework that this study is relying upon is relatively simple in terms of the mathematical formulation of the equations that govern the human dynamics. Nevertheless, it is rudimentary efficient to incorporate valid assumptions to the model which offers opportunities for correct interpretation of the results. By this formulation, the framework has descriptive, predictive and explanatory knowledge without make it substantial complex to developed it in simulation software. Lastly, another issue that is accentuated is the validation of the proposed model. As it mentioned numerous times, the difficulty, for the time being, is to measure and quantify the human factors and this fact makes us to face-validate the model at an aggregate level or by interpreting the results as valid because resembling the situation that we are studying.

1.8 OUTLINE

The methodology of this exploratory research is illustrated in figure 1.1 . In Chapter 2, we conduct an extensive literature review containing the effects of adverse weather conditions on macroscopic and microscopic levels pointing out the parameters of high importance. In the continuation of the same chapter, we provide fundamental behavioural theories in driving as well as some of the paramount importance mental-cognitive models are further elaborated. In Chapter 3 we discuss a possible extension of the IDM+ model to rudimentary incorporate kinematics vehicle kinematics characteristics that are useful for accounting for the effect of rainy conditions. The human factor(s) are modelled based on the seminal work of (Van Lint & Calvert, 2018) and further extended by integrating mental and physiological mechanisms that are speculated to be in effect during these adverse weather events. In chapter 4, we show the simulation scenario we conduct to assess the effectiveness of the modelling technique. In addition, we introduce response measurements (KPIs) of the model to interpret the results in terms of efficiency and safety. Lastly, scenarios are formed for each case based on the hypothesis we

1 The main source of data which is "abundant" in the loop detector data. The trajectories are hard data set to obtain.

made. In chapter 5, we present the results of each scenario while sub-conclusions accompanying each distinct case. Chapter 6 discusses the limitations of this study reflecting on the (large number of) assumptions that we made. Conclusively, in chapter 7, we answer the main research question of this study and lastly, in chapter 8, recommendations for further research and outlook are provided.

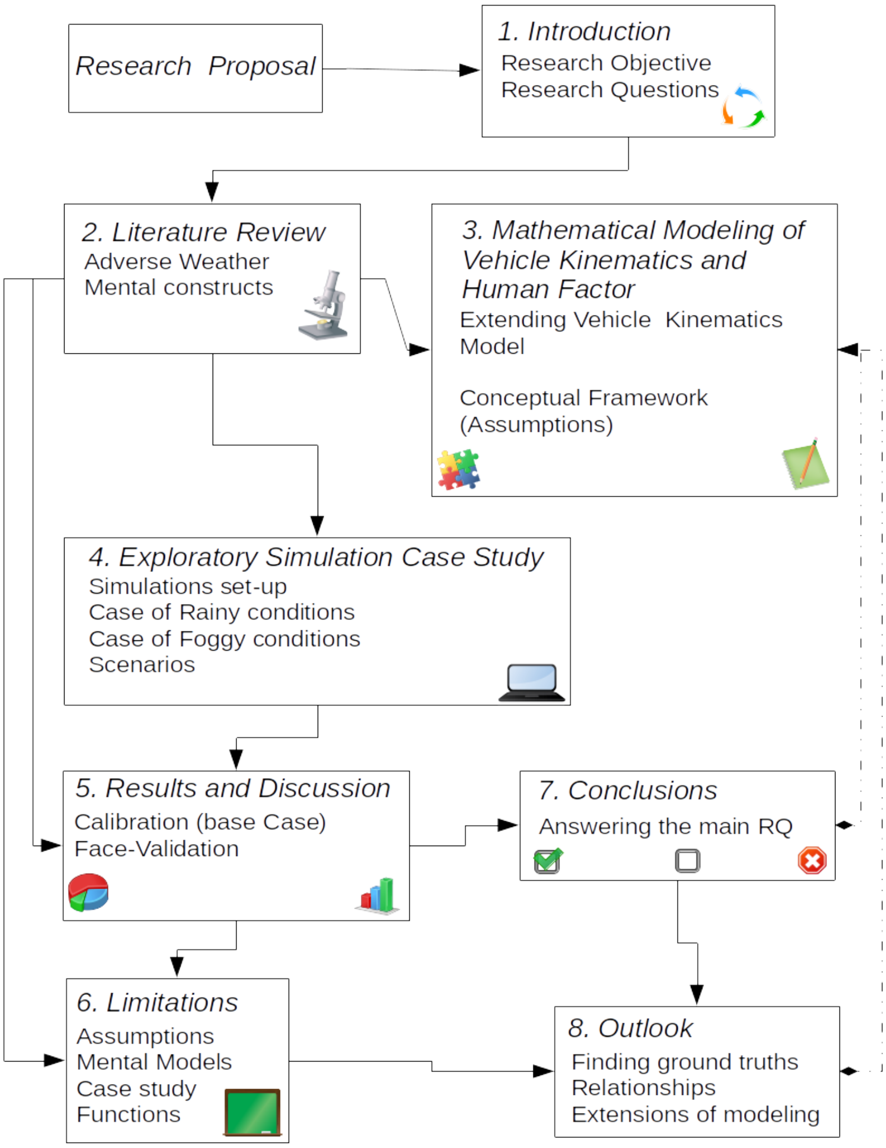


Figure 1.1: Outline of the thesis

2 LITERATURE REVIEW

In the present chapter, a literature study is performed in order to understand the impacts of the inclement weather on the road traffic performance on one hand, and the latest advancements of combining psychological constructs into simulation logic to generate and explain complex driving behaviour, on the other hand. As the reader suspects, the literature review will focus on some of the weather conditions and their impacts on the longitudinal driving behaviour, as a holistic methodological approach is not the object of the present thesis.
The chapter is composed of three sections. The first section illustrates the adverse weather events by giving definitions and then narrows down to macroscopic impacts of the traffic, especially on the fundamental variables of speed and capacity. At a microscopic level, the literature is restricted to the events of the rain and the fog. As we mentioned earlier, it is almost impossible to offer a holistic methodology, and hence the frequently studied events offers a good basis to start the research. The second section outlines human behaviour by showing the conceptual mental construct to represent the process of thinking. A basic understanding is firstly obtained by examining the mental construct of (Wickens et al., 2015). Then, the mental construct of (Shinar, 1978) and the situation awareness construct of (Endsley, 1995) are thoroughly described as will be used in the simulation study. The last piece of the human behaviour puzzle is that of (Fuller, 2005), (Fuller, 2011). These constructs are rather fundamental as postulating that the driving task is a function of perceptual processes and predefined standards. In the last section, the results of the literature review, the main takeaways and answers to the research questions are provided.

2.1 ADVERSE WEATHER CONDITIONS

At this point, it is crucial to define the adverse weather conditions and normal weather conditions. (Zhang, Holm, Colyar, et al., 2004) proposes that weather events are any meteorological occurrence that causes weather conditions to degrade from the ”ideal” weather condition. Ideal conditions are characterized by no precipitation, dry roadway, good visibility at the calibre of 0.4km, and winds less than 16 km/h. These adverse events are collectively known as; rainfall, snowfall, windstorm, fog, high/low temperatures, and flooding. These events emerge for a certain period causing deterioration of the performance of the road networks and even exert accidents to the road users (Stahel, Ciari, & Axhausen, 2014).
The weathers impacts on highway traffic are seen and measured in the dimensions of traffic demand, traffic safety, and traffic flow relationships, according to (Maze et al., 2006). Traffic demand may change after the introduction of inclement weather. This behaviour may lead to cancellation of trips, or the diversion of some others. Regarding traffic safety, the results seem to vary, but all of them lead to an increment to crash rates. In Iowa, for instance, the crash rates increased by 13 times during in moderate-intensity snowstorms and by 25 times in high-intensity snowstorms. This behaviour is attributed to the high winds, i.e. difficult manoeuvrability of the vehicle, and the low visibility, i.e. low perception of the environment, (Maze et al., 2006). From the traffic supply side, the freeway capacity seems to had a 14% reduction exposed to heavy rain intensity (more than 0.25 in/h) and 22% capacity reduction during heavy snow(0.5in/h), (Maze et al., 2006). Additionally, traffic operations have a higher risk in an accident. In the empirical study of the Federal Highway Administration in the U.S.A., (FHWA, 2020) between 2007 and 2016, 16% of crash fatalities attributed to the presence of inclement weather or slick pavement. Since we have built a basic understanding of the effects of the weather on traffic, the following sections unravel the effects on the macroscopic and microscopic levels respectively.

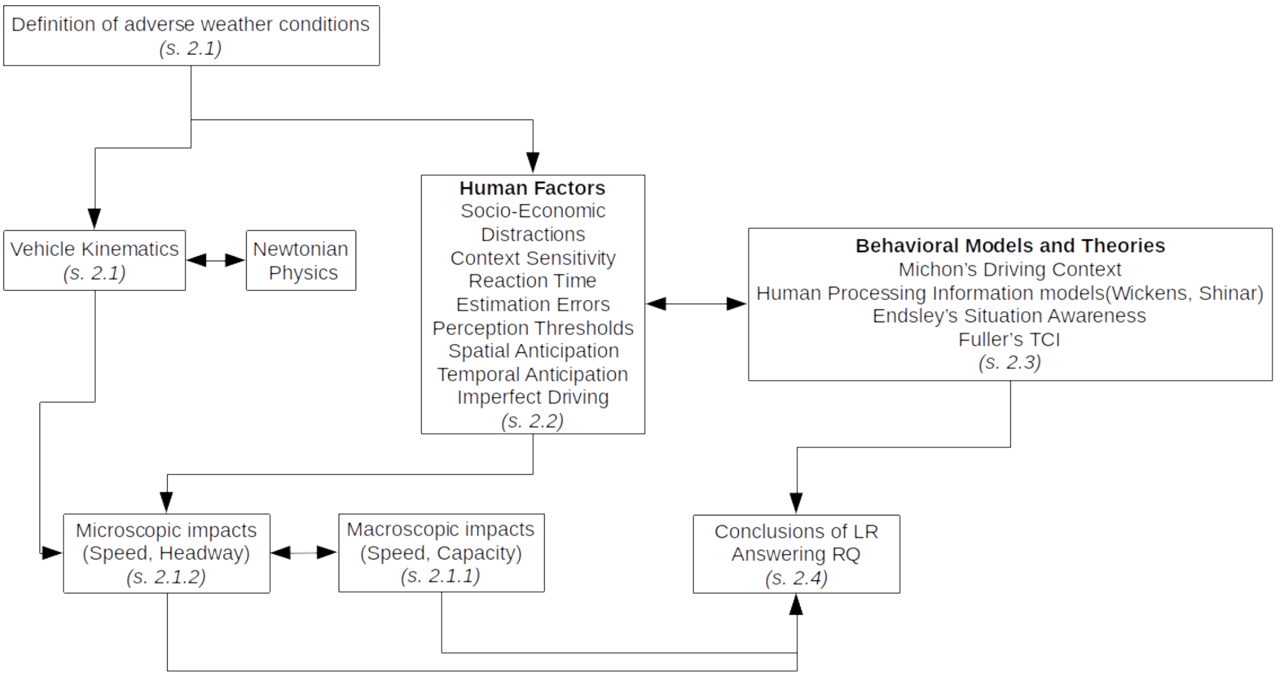


Figure 2.1: Literature review workflow concerning the three major domains of weather, behavioural theories, and simulation frameworks

2.1.1 Macroscopic Effects

The first quantitative results of a negative correlation between weather conditions and traffic flow was pointed out quite early, in 1950 by (Tanner, 1952). This relationship is of paramount significance to bear in mind as the proposed methodology in chapter 3 has as a basis this empirical evidence. Since then, a large body of literature has focused on the weather effects on the key parameters that impacted: the capacity, the speed, the traffic demand, and the delay. As mentioned before, the rain is the most influencing factor of the weather-related crashes. According to (FHWA, 2020), 46% of the crashes related to rainy weather during the period 2007 - 2016 in the U.S.A. Many empirical studies reside in the literature for assessing the impacts of rainy conditions, (Maze et al., 2006),(Hou, Mahmassani, Alfelor, Kim, & Saberi, 2013), (Billot, Faouzi, & Vuyst, 2009),(Chung et al., 2006), with the vast majority focusing at the macroscopic impacts. In the followings, we review the findings of the literature studies affecting the key parameters.

- **Capacity**

  In the analysis that was conducted by (Hranac et al., 2006) with empirical data from loop detectors in the U.S.A., the followings conclusions drawn regarding the precipitation of rain and snow. The light rain (0.01cm/h) leads to 10-11% capacity reductions. However, the capacity was not affected by the increasing intensity of rain and thus remained constant. The precipitation with snow showed further reductions in capacity in a range of 12-20% when the intensity of snow is 0.01cm/h. Similarly, with the rain, no further capacity reductions were observed as the intensity of snow increases.

  Roughly the same results are derived in the study that was conducted in Twin Cities (U.S.A.) of (Maze et al., 2006) at its freeway system. The raw data were originated from inductive loop detectors(single loop detectors) that monitor the occupancy and volume of the vehicles. For the different intensities of rain (0–0.01 in./h, 0.01–0.25 in./h, ¿0.25 in./h) was find that the capacity hindered to (2, 7, 14 %) respectively. For the weather event of snow with intensities (¡=0.05 in./h, 0.06–0.1 in./h, 0.11–0.5 in./h, ¿0.5 in./h) the capacity of the freeway reduced with (4, 9, 11, 22%). For the event of fog, the capacity reduced with (10, 12, 11 %) for visibility distance (1–0.51 mi, 0.5–0.25 mi, ¡0.25 mi) respectively. Regarding the wind intensity, there were no substantial changes. Solely 1% changes from the ideal conditions. However, this change could be attributed to the stochastic nature of the capacity and not to the weather phenomenon itself. Similarly, capacity reductions of 8% are showed when the temperature reaches -20° Celsius. There is an assumption that the friction of the road hindered due to the ice on the road tarmac.

In Istanbul, Turkey, similar findings were shown in the study of (Akin, Sisiopiku, & Skabardonis, 2011). The historical data extracted from loop detectors contained the volume and speed for the two freeway corridors in the Istanbul metropolitan area. Generally, the rainy conditions led to 6-7% capacity reductions while the presence of little snow, fog and haze did not affect the capacity. Nevertheless, the intensity of the later weather phenomena did not register in the study, and hence no safe conclusions can be derived.

In the empirical study conducted on a two-way interurban freeway section near Paris, France data were collected from nine dual-loop detectors between the years 2005-2007 (Billot et al., 2009). The only weather event was assessed it was the rain for intensities (2 mm/h, 2 mm/h - 3 mm/h, and 3 mm/h) namely light, medium and heavy intensity respectively. Calibrating a multivariate, single-regime model of (Van Aerde & Rakha, 1995), the study concluded that the capacity deduced from 18.5% to 21%.

An extended empirical study performed in Japan, Tokyo Metropolitan Expressway, in various locations such as weaving sections, curves, and circular routes by (Chung et al., 2006). The rain intensity was spanning between a low of 1mm/h to the extreme of 20mm/h. In the site of Horikiri junction where is the meeting point of two expressways, the capacity reduced from 4-9%. The same incremental trend follows the rest locations of the study, Sangenchaya, Daikancho, Yoyohi, and Hamasakibashi. At the later location the reductions in capacity is 6% for low intensity rain and 14% for high intensity rain(10-20 [mm/h]).

In The Netherlands, a recent study of (van Stralen et al., 2015) indicated capacity reductions to various locations of the Dutch motorway system. To expand further, by applying the methodology of (Kaplan & Meier, 1958) the capacity reductions in light rain (0.01-1 mm) were on average 5.7% and in heavy rain (¿1mm/h) was 8%. These results are in good agreement with the findings of (S. C. Calvert & Snelder, 2013) conducted in The Netherlands and the analysis realised with the same method. However, in the first study, the capacity at the bottlenecks is robust over the course of the years without any significant changes. The authors suspect that a contributory factor for this is the road surface and hence more research indicated towards that direction.

In the ensuing, conclusions are drawn regarding capacity and rain intensity. By and large, the rain has a negative correlation with the roadway capacity. As we admit, various empirical studies have been performed showing that the rain hinders the capacity from 1 - 21% with the normal operations. The resluts of the literature review are shown in Table 2.2. The reduction of the capacity differs amongst the various locations as there are more determinants which define the degradation magnitude. To name a few, such as the infrastructure quality, the driving rules, the vehicle's technology.

- **Speed**

A first consistent attempt to understand how the rain, fog, and high winds affect driver speeds was endeavoured by (Kyte, Khatib, Shannon, & Kitchener, 2001) in the U.S.A. under the Idaho storm warning project. The project was initiated after 18 major traffic accidents that involved 91 vehicles, nine fatalities and 46 injuries during the years of 1988 and 1993 along a rural section of I-84 to the southern-east of Idaho. This project deployed sensors measuring the traffic, visibility and weather conditions. The weather classification follows a general description of wet pavement, snow pavement, high wind and low visibility.

Table 2.1: Literature Review of the Effects of Rain on the Speed and the Capacity

Weather Event	Study	Type	Year	Country	Speed	Capacity	Comments
Rain	*Kyte et al*	Empirical	2001	USA	WP[1]:8-13% HW[2]:9% 0.77km/h [3]	Not included	
	Agarwal et al	Empirical	2005	USA	MSP (<0.01in/h):2.43% (0.01-0.25in/h):4.6% (>0.25in/h):6.85% MIC (<0.01in/h):2.09% (0.01-0.25in/h):4.23% (>0.25in/h):6.67% STP (<0.01in/h):1.27% (0.01-0.25in/h):2.81% (>0.25in/h):4.49%	MSP (<0.01in/h):1.44% (0.01-0.25in/h):5.67% (>0.25in/h):10.72% MIC (<0.01in/h):1.17% (0.01-0.25in/h):5.94% (>0.25in/h):14.01% STP (<0.01in/h):3.43% (0.01-0.25in/h):10.10% (>0.25in/h):17.67%	
	Maze et al	Empirical	2006	USA	(0–0.01in/h):2% (0.01–0.25in/h):4% (>0.25in/h):6%	(0–0.01in/h):2% (0.01–0.25in/h):7% (>0.25in/h):17%	
	Chung et al	Empirical	2006	Japan	(0-1mm/h):4.5% (1-2mm/h):4.6% (2-3mm/h):5.6% (3-4mm/h):6.4% (5-10mm/h):8.2%	(1mm/h):4.0% (2mm/h):4.1% (3mm/h):5.2% (4mm/h):5.4% (5mm/h):7.9% (5-10mm/h):8.9% (10-20mm/h):9.7% (>20mm/h):9.6%	The reduction on speed and capacity regard the median value between the sites Sangenchaya, Daikancho, Hamasakibashi, Korikiri, Yoyogi.
	Billot et al.	Empirical	2009	France	(2mm/h):8% (2-3mm/h):12.6%	(2mm/h):18.5% (2-3mm/h):21%	The recordings of heavy rain neglected as incomplete data.
	Akin et al	Empirical	2011	Turkey	Rain : 8-12%	Rain : 7-8%	
	Calvert et al	Empirical	2013	The Netherlands	-	1.9% per mm/h capacity reduction	Margins of rain intensity are between 1mm/h up to 5mm/h
	Van Stralen et al.	Empirical	2015	The Netherlands	-	(0.01-1mm/h):4-9% (>1mm/h):4-11%	
	Chen et al	Simulator	2019	China	(0–9.9)mm/24h:3.1% (10–24.9)mm/24h:2.0% (25–49.9)mm/24h:7.6% (100–249)mm/24h:7.6%	(0–9.9)mm/24h:8.3% (10–24.9)mm/24h:+1.2% (25–49.9)mm/24h:3.4% (100–249)mm/24h:13.5%	

To begin with, we choose the low visibility how affects the human driver, given that all the rest weather conditions are ideal i.e. the pavement is dry, and the wind is less than 24 km/h. Although there is a mere contradiction to what we defined as ideal conditions regarding the wind speed as we state above (Zhang et al., 2004). When the visibility is greater than 1km, the speed remains the same on average at 121 km/h. For impaired visibility, the speed gradually decreased and reach 106.2km/h when the calibre is up to 0.3km. The wet or snow-covered pavement introduces speed reductions up to 10 to 16 km/h and 50k/h speed reductions for heavy snow. The combination of the snow-covered tarmac, low visibility and high winds result in 35-45 km/h reductions.

In the study of (Agarwal, Maze, & Souleyrette, 2005), the authors put into scrutiny three distinct systems that monitor: (i) the traffic flow between the Twin Cities in the U.S.A. (4000 loop detector collecting the occupancy), (ii) the weather by automated surface observing systems(ASOS), (iii) the conditions of tarmac by the road weather information systems(RWIS) with the objective to identify the changes of the speed, headways and capacity during adverse weather events. The rain data divided into 4 bins of (0, less than 0.01, 0.01–0.25, and greater than 0.25 inches/hour. The findings illustrating that the speed reductions for the later three weather contortions are 1%–2%, 2%–4%, and 4%–7% respectively. Worth mentioning that the statistical differences between the later two weather conditions are not significant. Following to that, the analysis of snowy conditions shows that speed reductions of 35%, 7%–9%, 8%–10%, 11% - 15% for trace, light, moderate and heavy snow (less than/equal to 0.05, 0.06–0.1, 0.11–0.5, and greater than 0.5 inches/hour).

(Hranac et al., 2006) revealed the same results as (Agarwal et al., 2005) for the same location, Twin Cities, USA. The light rain(0.01cm/h) impacts the free-flow speed and the speed at capacity with 2-3.6% and 8-10%. For rain intensity of 1.6cm/h, the same speed variables suffered from 6-9% and 8-14%. Snow shows higher reductions for the variables of free-flow speed and speed at capacity with 5-16% for 0.01cm/h snow, while 5-19% when the snow intensity reaches and surpass 0.3cm/h.
Approaching the problem from the perspective of a driving simulator, the study of (Chen et al., 2019) has to offer rich insights. The study considers the phenomena of fog, rain and snow. For the first phenomenon, the speed was not affected substantially, on the contrary, it seems that the speed was fluctuating for visibility distances between 300-10000m. Notwithstanding, when the visibility is less than 300 m, the speed was suffered 27.5% reductions. When it comes to rain, the reductions start from 3.1% up to 7.6%. The most striking reduction is observed for the snow weather event with values 19.2% and 45.6% for intensities (2.5–4.9)mm/24h and (10–19.9)mm/24h respectively.

Table 2.2: Literature Review of the Effects of Snow on the Speed and the Capacity

Weather Event	Study	Type	Year	Country	Speed	Capacity	Comments
Snow	*Maze et al*	Empirical	2006	USA	(<=0.05in/h):4% (0.06-0.1in/h):8% (0.11-0.5in/h):9% (>=0.5in/h):13%	(<=0.05in/h):4% (0.06-0.1in/h):9% (0.11-0.5in/h):11% (>=0.5in/h):22%	
	Hranac et al	Empirical	2006	USA	(0.01cm/h):5-16% (0.03cm/h):5-19%	(0.01cm/h):12-20%	
	Agarwal et al	Empirical	2005	USA	MSP (<=0.05inch/h):3.8% (0.06-0.1inch/h):8.98% (0.11-0.5inch/h):8.56 (>0.5):11.20 MIC (<=0.05inch/h):3.58% (0.06-0.1inch/h):8.56% (0.11-0.5inch/h):10.52 (>0.5):15.56 STP (<=0.05inch/h):5.14% (0.06-0.1inch/h):7.02% (0.11-0.5inch/h):9.11 (>0.5):13.62	MSP (<=0.05inch/h):3.93% (0.06-0.1inch/h):9.03% (0.11-0.5inch/h):7.45 (>0.5):19.53 MIC (<=0.05inch/h):5.51% (0.06-0.1inch/h):11.53% (0.11-0.5inch/h):12.33 (>0.5):19.94 STP (<=0.05inch/h):3.44% (0.06-0.1inch/h):5.48% (0.11-0.5inch/h):13.35 (>0.5):27.82	
	Chen et al	Simulator	2019	China	(2.5–4.9mm/24h):19.2% (10–19.9mm/24h):45.6%	(2.5–4.9mm/24h):37.9% (10–19.9mm/24h):67.6%	

The rain and the speed of the traffic has a negative relationship like the capacity. The magnitude of degradation is between 2 - 12% in the vast majority of the studies. As a predominant underlying reason for the speed reductions is the degraded friction coefficient of the roadway. The vehicles lose an amount of manoeuvrability and as a compensation mechanism, drivers slow down.
The fog also affects the capacity and the speed of the road operations. A negative relationship is shown in Table 2.3. The fog is to a lesser extend studied in the literature even if the negative results in traffic operations are evident. The intriguing while an interesting result of the fog is the deterioration of visibility leading a human driver to suffer perceptual errors in judging speed and distances and assumed compensation mechanisms to increase the safety while reducing the risk. The aggregate reductions on speed and capacity of such behaviour are illustrated in Table 2.3. Reductions up to 32% on speeds and 12.5% on capacity.

Table 2.3: Literature Review of the Effects of Fog on the Speed and the Capacity

Weather Event	Study	Type	Year	Country	Speed	Capacity	Comments
Fog	*Maze et al*	Empirical	2006	USA	(1-0.51mi):7% (0.5-0.25mi):7% (<0.25mi):12%	(1-0.51mi):10% (0.5-0.25mi):12% (<0.25mi):11%	
	Hranac et al	Empirical	2006	USA	-	10%%	When the visibility declines from 4.8 to 0.0 km
	Akin et al	Empirical	2011	Turkey	Negligible Effects	Negligible Effects	
	Brooks et al	Simulator	2011	USA	(31m):4% (18m):15.3% (6m):32.8%	-	Differents scenarios were tested, the one we choose to show the results is namely number 4.
	Chen et al	Simulator	2019	China	(>=1500m): +5.3% (1500-800m):+3.6% (800–300m):+0.1% (300–50m):27.5%	(>=1500m):+0.9% (1500-800m):+1.4% (800–300m):+1.1% (300–50m):-12.5%	

2.1.2 Microscopic Effects

The main focus of the research was to describe and explain the effects of the inclement weather at a macroscopic level by using empirical data. The documentation is enormous in that direction. Thereafter, endeavours to generate this behaviour under such conditions are in the spotlight of research and practice. The options to cope with such a problem is to include amongst others, controlled experiments on the road, traffic simulator experiments, and simulation studies. The latter approach is tricky, as demands apart from the sufficient models of longitudinal and lateral movement, a model(or a representation) that captures the human factor.

The focus of the present study is on the **longitudinal motion** which describes and explains the vehicle's movement on the traversing direction under the weather phenomena of fog and rain. The following part unravels to the reader what are the effects of the adverse weather on the time headways and the speeds. Variables that are observable, measurable and form the outcome for the most car-following models (Rakha et al., 2010). Also, traffic safety is outlined to some studies as a measure for further understanding of the inclement weather events. The vast majority of the reviewed studies include simulator experiments in combination with modelling approaches that generate and explain such behaviour.

The purpose of further understanding and modelling the system of the vehicle, human driver and environment are getting direr with the advancements of the automated vehicles. From a traffic engineering perspective, we aim at modelling accurately and precisely the traffic operations in such a mixed environment. That will help, ultimately, to assess the "real" effects of the automated vehicles in traffic operations. Before going there, we first need to understand what are the effects of the inc element weather both on the driver and the vehicle. To the ensuing text below we review the effects of rain and fog.

Rain:

What we witness during intense precipitation is that the drivers overtake less and engaged into lower speeds in order to create large space distance (SWOV, 2012). Contrary to this adaptation, the risk of having an accident is higher during rainy weather than dry weather though (SWOV, 2012). These empirical evidences reveals the increasing complexity of weather events on the traffic.

A good starting point to understand the influence of the rain at a microscopic level is in the study of (Hogema, 1996). This study investigates how the drivers change their behaviour under rainy conditions. The two factors that the study indicates is the reduced visibility and/or the degraded grip between the vehicles' tires and the asphalt. As a data-driven study, the area that investigated was the A16 motorway near the city of Breda. The motorway has two distinct streams composed by two lanes each. The maximum speed limit is restricted to 100km/h while the maximum throughput of traffic does not surpass its capacity. The car-following variables the study considered are headways and Time-To-Collision(TTC). The rain intensity categorized into light(<=1mm/h), moderate(<=5mm/h) and heavy(>5mm/h) while filtering criteria regarding unusual phenomena, very low visibility and advisory systems from the wayside as well neglected. The ANOVA analysis yielded that the percentage of vehicles driving with <1s headways were smaller under rain conditions than in dry. The same pattern observed for those vehicles with <3s headways, whereas the vehicles having ¡5s headways were not affected by the external conditions. For the second variable, that is the TTC, the percentage of the vehicles having TTS<5s is smaller in rainy conditions than in dry. The same conclusion was drawn for the vehicles having TTS<10s.

(Billot et al., 2009) in a multilevel analysis framework shows the individual behaviour of the vehicles in terms of time headways, space headways and speeds. The data were provided by the West Paris Regional Laboratory for the years 2005 to 2007 from nine double-trap loop detectors. The event of rain categorized further into light(2mm/h), moderate(2-3mm/h) and heavy(up to 3mm/h). Nevertheless, the last category was omitted because of the inability to obtain data. From the analysis, it is clear that the higher the intensity of rain is, the higher the drop of the speed is. In terms of frequency and regarding the short TH on the slow lane, a drop of 12.1% of the TH ¡ 2 s is observed under rainy conditions (light rain). In moderate rain intensity, a substantial decrease of more than 18% is observed. This drop is reported on a rise of the TH between 2 and 10 s. The authors provide modelled time headway distributions fitting a log-normal distribution. They pointed out that the mean time headway under moderate conditions increased up to 1.07[s] and 1.24[s], and 39.3% from dry conditions).

Under the same results are the findings of (Samoili, Bhaskar, Hai Pham, & Dumont, 2011) with 0.8[s] mean headway under dry conditions to increase of 1[s] under rainy conditions. The most important takeaways of this study is a drop of 18% of the time headways less than 2[s] and a decrease of 20% of the spacing less than 50[m]. A modelling attempt by the authors was realised by the use of a log-normal distribution. The results showed that this fit performs the best amongst the available data.

Until this point, we have seen that the offered literature unravels data-driven methods and make use of rudimentary modelling approaches in order to prove the differences between dry and inclement weather statistically. Having this as a reference point, the researcher creates a framework for further exploration. To that end, various studies have been explored by incorporating microscopic car-following models to include the characteristics that the adverse weather posed to the system of the road network. One of them is the study of (Hammit, Ghasemzadeh, James, Ahmed, & Young, 2018) in which used the naturalistic data-set of SHRP2. After proper processing of the available data set, the authors illustrate six weather conditions; in this section, we are concentrating only in the event of rain which categorized into very light rain, light rain, moderate rain, and heavy rain. The car-following model of Gipps was exploited in their study and calibrated using a genetic algorithm technique. The results of the calibration yield to an increased reaction time. Particularly in the event of heavy rain with we observe a difference of 0.9s, almost doubled, from the base case. The desired speed is not changing considerably over the various intensities of rain. The maximum acceleration affected the most with a decreasing trend as the intensity of rain increases. For the desired deceleration and the estimated desired deceleration, there is not much difference to highlight. Moreover, the mean time headway analysed for the various weather intensities. The increase of the headways is 8%,13% and 16% for very light, light, and moderate rain respectively. There is an 11% increase in the case of heavy raining while someone expects a higher increase of headways. From the safety perspective, the time-to-collision was utilized. TTC is susceptible to specific scenarios and it had large variations. Albeit this fact, the findings outlined that the drivers governed by aggressive behaviour in high-intensity rain conditions. The authors indicated that a possible explanation is the high values of reaction time and the less efficient manoeuvrability.

There are endeavors to explore more aspects in longitudinal,(Soria, Elefteriadou, & Kondyli, 2014), driving by investigating the traffic conditions, the weather conditions, and the driver heterogeneity characterized as aggressive, average and conservative. As a data-driven method, the study exploited the trajectory data of the vehicle provided by University of Florida (TRC). Even if in this study the calibration procedure is taken place 4 times sequentially, ne time for each corresponding dimension, it is pinpointed that we have to consider the heterogeneity of the drivers and the different traffic conditions as they yield to better representation of the traffic conditions.

Fog:

In the recent study of (Yan, Li, Liu, & Zhao, 2014), three levels of risk were investigated under the presence of various intensities of fog by using a driving simulator was performed. The fog conditions were namely, no fog, light fog and heavy fog with visibility of 250m and 50 m for the two latter conditions. Three risk levels allocated into an equivalent number of parts of the mock circuit-roadway. A straight road, uphill road, downhill road and s-type road segment constitutes the geometric road characteristics. The low-risk driving scenario investigated the effects of foggy conditions on basic speed control, including geometric characteristics of the road such as uphill, downhill and s-type segment. The speed limit on the straight segment was 80km/h, 50km/h for the uphill and downhill and 30 km/h for the s-type segment. The medium-risk driving scenario regards the speed behavioural adaptation of the following vehicle to the leading one. There were two stages in this scenario in which the leading vehicle accelerated from 30km/h to 65 km/h, and then decelerated from 65km/h to 10 km/h with rate -5m/s^2. The last scenario named high-risk was coined to investigate the behaviour of the drivers exposed to a pedestrian crossing the road. The pedestrian suddenly crossed the road at a speed of 15km/h. The time needed by the pedestrian to reach the centre line of the road was 3.5s. By this emergency event, the authors investigate the TTC for the various participants. The maximum speed limit at this segment is 80km/h. In the basic speed control scenario, the results revealed that the driving speed is substantially affected by the fog leading the drivers to slow down from 68.10km/h to 45.43km/h and 45.84km/h for light and heavy fog respectively. The speed of the driver to the rest of the geometric characteristics of the road was not affected at all. To the second scenario, the results illustrate that the fog does affect driving speed behaviour. The acceleration rate of the drivers under no fog conditions and in the acceleration stage was the largest, while in the presence of fog the acceleration rate of the drivers' declines as the fog intensity increases. Likewise, the same pattern was found for the average speed. In the deceleration stage, the average deceleration rate is the largest when there is no fog and decreases as the fog intensity increases. This compensation mechanism of reducing the speed is pointed out above, although from the experiment it seems that the drivers have better manoeuvrability of the vehicle as they are more sensitive to the changes. The last scene of the emergency response conveys that the drivers respond to the stimuli at 35m before the conflict point in clear conditions while the response length decreases at 25m and 20m in the light and heavy fog. In total, 17 crashes observed, four in no-fog conditions, six in light fog conditions and seven in heavy conditions.

In the study of (Broughton et al., 2007) the main objective was to understand the car-following behaviour and the decision habits of the drivers under three visibility conditions and explain how to avoid rear-end crashes. The experiment composed of a large population of licensed drivers and realized in a driving simulator. The three visibility conditions were namely, clear, moderate(limit 93m), and dense(limit 41m). The results showed that the mean time headway of the drivers, when the experiment performed for speeds no more than 30mph, increased slightly. On the contrary, for mean speed 50mph, the mean time headways increased dramatically for both fog conditions as a mechanism to compensate for the reduced visibility. Interestingly, the participants of this experiment categorized further to "laggers" and "non-lagers". The laggers are the participants that not followed within the range of visibility and non-laggers otherwise. For the second group, it was found that, when the experiment carried out at 50mph, the mean time headway was decreased to 1[s]. For the low-speed scenario, the mean headway remained the same over the different visibility scenarios. However, for high-speed , the laggers showed high variability of the mean standard deviation, as they are more sensitive to the changes of the leading vehicle.

In another simulation study conducted by (Hamdar, Qin, & Talebpour, 2016), it was considered the effects of the geometrical characteristics of the road in combination with the inclement weather. The general framework of the study constituted by a large number of parameters regarding two main categories; the so-called external factors and the cognitive factors. Our interest is on the weather which the authors illustrated that the most frequent weather events disturb the visibility of the drivers and imminently, depend on the intensity of the precipitation event, the asphalt surface becomes more slippery. Apart from these factors, they included and analysed additional factors. The fog showed that there was having no significant effect on the desired speed of the drivers. The statistical measure of the standard deviation of the speed was greater in foggy conditions than this in the normal conditions. The authors suspected that the low visibility contributed to the uncertainty of the drivers to estimate speed and distances and that lead to these observed speed fluctuations. Regarding the time headways, the drivers kept their headways relatively high, when driving in low visibility conditions.

On the other hand, when the visibility of the following drivers include the vehicle downstream, an interaction starts happening in the decision-making process, and thus the drivers follow the leader at lower distances. Concerning the reaction time and the indicator of time to collision, the study points out that when the visibility is low, up to 65.62ft, the TTC indicator was 3.02s. The indicator of the maximum acceleration was also used in the study to indicate the behaviour of the drivers. In low visibility conditions, the maximum observed deceleration was 1.68[m/s^2] for low visibility conditions. The same values found to the rest of the visibility conditions. That said, the values indicate the impaired capabilities of the drivers to judge properly the stimuli of the environment.

As the reader may realize, the speed is a prominent indicator regarding the adaptation of the drivers when driving under foggy conditions. In another driving simulator experiment of (Brooks et al., 2011), the driving performance was investigated under various intensity conditions of fog. The average speed between the four maximum visibility conditions was decreased from 91.3km/h to 89.1km/h. To the last two foggiest conditions, the speed was 82.9m/h and finally 71.7km/h. The apparatus of the scenario which tested was included indications for speed reductions or increments or maintain the speed. Furthermore, some scenarios included a task priority for lane keeping, pedestrian identification or maintain the speed at 55m/h to assess the responsiveness of the driver. The results for the different scenarios were very similar, but the most conservative scenario wherein no indicators were present, there ware task priorities and the consultation from the speedometer was available, revealed the lower average speeds. In this experiment, across all the variations of scenarios, the drivers tend to keep high speed except if the lane-keeping task was considered critical to the driving task. Another interesting takeaway of the study is that the drivers cannot react timely in a possible collision with an object. As an example, one can consider the scenario when a user drives traversing at a speed of 24.8m/s2 and the visibility is 31m. To react, in time, and get the vehicle in a complete standstill position, the deceleration which may use is 9.92m/s2. A relatively unrealistic and high deceleration.

Psycho-spacing models are well-known in traffic science as they account for relationships between the relative speed between the follower and the leader at some predefined action points. A close look at such a model when considering the fog in a driving simulator was undertaken by (R. G. Hoogendoorn et al., 2011). That research aimed to find how an adverse event such the fog affect the action points for the parameters of relative speed and distance, the acceleration at that points, and the "jumps" in acceleration. The first findings on the delta-v and spacing under normal and foggy conditions indicated that there is a statistical significance of the results. The results indicated that the drivers reacted on larger values of Δv. The authors contemplated that this effect is derived from the inability of the drivers to react to smaller differences on the stimuli due to the impaired vision. Also, they accentuated that the original model is incapable to account for this specific weather event in its original formulation. For the jumps in acceleration, it was found that the driving population was reacting parsimoniously in the case of an adverse event. The study concluded that the error of the fitted models in the case of fog was larger compared to normal conditions. This fact entails that deterministic perceptual thresholds are unrealistic.

Sub-conclusions

In retrospect, we conclude to the followings regarding the microscopic effects of the rain and fog. Rain imposes a substantial difficulty in driving task as the friction coefficient is degraded. Empirical analyses and simulations yielded that rain triggers adaptation effects to the drivers. Two compensation responses emerge, an adaptation of the time headways and the desired speed. Usually, the traffic follows the conservative strategy of slowing down. The performance of the traffic stream is affected as well. The maximum acceleration and deceleration are less in magnitude than in these observed in normal weather conditions. Some of the studies indicate that the reaction time of the drivers is affected as well. Heterogeneity between the driving population is a key determinant to model the car following behaviour with greater accuracy.

Foggy conditions are also challenging. The studies derived that the drivers seem to suffer from perceptual errors. These errors lead the driver to overestimate the speed and the distance of the leading vehicle. The compensation mechanisms which we acknowledge here are adaptations to the headways and the speeds. Most drivers seem to slow down and/or create a larger headway with their leading vehicle. There is a contradiction, wherein some studies indicate that some other drivers following their leader. In this behaviour, we witness a more aggressive driving with high variability in the acceleration and deceleration. The driver's reaction time is also affected to make them lagging to their decisions due to the reduced visibility.

2.2 HUMAN FACTORS

The present section aims to elaborate on the human factors that are inherited to every driver and affect human driving, predominately, at an operational level. In order to understand which factors prevail under the driving task, it is important to look at fundamental theories on Human Information Processing.

Over the last years, it is accepted widely that the car following models have been developed so far are not adequate to describe or explain all traffic conditions observed in the field. The reason for that is that the HF is usually neglected or modelled at a rudimentary level. By rudimentary level, we mean, for instance, that in the IDM model the only HF is the reaction time and marginally the maximum acceleration. Someone could argue about the desired speed, but given the ACC controllers can execute the same process with better performance, we argue that the reaction time is the only HF trait. These factors are elaborated in the followings to understand their importance and how they modelled at a simulation environment. According to (Saifuzzaman & Zheng, 2014) and (Treiber & Kesting, 2013a) HF that included or potentially can be incorporated are; socio-economic factors, distractions, context-sensitivity, reaction time, driving skills, estimation errors, perception thresholds, spatial and temporal anticipation, aggression, imperfect driving, driving skills and drivers' preferences and desires.

2.2.1 Socio-Economical Factors

A driver is affected or guided by the so-called socio-economical factors in their driving behaviour. These factors are the age, the gender, the level of education, the family background etc. In some simulator studies, we have seen that the effects of the gender on the speed variability is concerned, (Broughton et al., 2007). This study had indicated that in extreme foggy conditions the speed variability of the male drivers is twice as large to the variability of the females. Generally, the socio-economical factors in simulation studies is still neglected even if the impacts on the traffic safety are evident, (Lindorfer, Mecklenbraeuker, & Ostermayer, 2018).

2.2.2 Distractions

Distraction in driving is one of the most influential factors that lead to degradation of performance and even to accidents. The first common consensus about what distraction is in the driving operational domain was offered by (Hedlund, Simpson, & Mayhew, 2006), defining that it is*"a diversion of attention from driving, because the driver is temporarily focusing on an object, person, task or event not related to driving, which reduces the driver's awareness, decision-making ability and/or performance, leading to an increased risk of corrective actions, near-crashes, or crashes"*. Since then, the definitions given from various authors seems to be at the same frequency, like the one given by (Lee, Young, & Regan, 2009), (Van Lint & Calvert, 2018), and (Regan, Hallett, & Gordon, 2011). The last authors pointed out that the distraction regards the driving behaviour per se, the human driver traits, the activities that divert drivers attention, and the external environment conditions. At a mathematical modelling level, insofar, distraction has been modelled in a few case studies. The first case study is one of a rubbernecking in an accident situation, (van Lint, Schakel, Tamminga, Knoppers, & Verbraeck, 2016). The rationale here is that the distraction is varying while a human has a visual on the accident location. The assumptions are two; the desired speed drops and the reaction time increases when a driver is within its visual calibre. The mathematical formulation is straightforward two aforementioned parameters. In another recent study, the distraction is divided into two categories, the major and the severe distractions, (Lindorfer et al., 2018). This in turns, affects the reaction time of the drivers by introducing a reduction factor and decreasing the velocity of the driver. For the severe distractions, like the ones that a driver experiences when consulted by a navigation system, the mathematical formulation disregard to update the control parameters(the speed, the distance and the relative speeds in this case) for the time that the distraction lasts. Another formulation has been seen in the study of (Van Lint & Calvert, 2018) when the distraction is a factor that affects the Task Demand and hence the performance of driving. In this study, there are two distinct levels of mathematical formulation. The one-level regards the car-following behaviour, while the other level concerns about the behavioural dynamics of a human driver. The distraction is embedded in this framework as an additional task demand and interacts with the perception, the cognition, and the response on the decision variables of movement.

2.2.3 Context Sensitivity

The surroundings of the vehicles have a crucial role in driving behaviour. According to (Oppenheim & Shinar, 2012) the environment parameters that affect the driving behaviour are the road (road type - number of lanes- ,alignment, surface conditions), the traffic, and the visibility under inclement weather. For the latter parameter, even if the drivers change their speed to compensate for additional headway, this adaptation exerts the driving performance momentarily,or as long the weather phenomenon prevails. When driving in a congested state, most of the drivers seem to lose their level of alertness, their response deteriorates while the time gaps increase. According to (Treiber & Kesting, 2013a), this impediment in driving performance owning to these surrounding conditions could serve a possible explanation for the phenomenon of the capacity drop. In the simulation studies, the overall effect can be reproduced by tweaking of a model's parameters. For example, when simulating a traffic flow with the IDM, the phenomenon of the capacity drop is observed when the acceleration is reduced while the the reaction time is increased (Treiber & Kesting, 2013b). To some extend, this modification accounts for context sensitivity environment. In this line, in the study of (Lindorfer, 2019) suggests different reaction times of a driver depending on the traffic regime that a driver is. By following this modelling approach, the context sensitivity of the environment is considered.

2.2.4 Reaction Time

Reaction time has been seen in many studies in the past as it is a parameter highly connected with human nature, (Treiber et al., 2006),(Saifuzzaman & Zheng, 2014). In the mid 19^{th} century, the Dutch physiologist named Donders started to speculate about the central processes involved in choice and recognition reaction times. Since then, numerous models have been proposed. Maybe the most dominant one stems from the experimental psychology field having a linear form. Is a combination of the minimum reaction time of a modality and the number of alternatives that someone has to sort out to decide their response[4]. Reaction time from (Treiber & Kesting, 2013a) can be seen as the composition of the mental processing time, the movement or action time, and the technical response time. The first time can be further elaborated into sensation time, recognition and interpretation time, and decision time. Similar logic followed in the paper of (Van Lint & Calvert, 2018) introducing that the reaction time consists of physical reaction time and the attention lag-time. The first time is the result of the perception and comprehension stage of situation awareness while the latter is the result of the additional information processing. The reaction time varies among the driving population due to the social factors that depend on the age, the experience of the driver, **the visibility conditions**, degree of surprise, and the urgency of action. Due to its nature, many researchers implement a straightforward formulation to the car following models, (Lindorfer, 2019),(Treiber et al., 2006) considering the GHR model and their extensions, predominantly the desired measures models, the safety distance models, and the optimal velocity models, (Saifuzzaman & Zheng, 2014). The most common way to introduce finite reaction time to a model is to include a quantity of finite reaction time, (Treiber et al., 2006). Should the reaction time is an integer multiple of the time step, the equations can be solved simply by estimating the relevant quantities. Should not, a linear interpolation is proposed,(Lindorfer et al., 2018).

2.2.5 Estimation Errors

Estimation errors related to the inability of a human driver to estimate the stimuli of interest (gaps and speed difference) successfully. The factors that are influencing the inherited inability to estimate the stimuli are the driving context, the driver characteristics and the surrounding environment such as visibility conditions (Treiber & Kesting, 2013a). Contributing factors to imperfect estimation errors are the adjacent vehicles, the visibility

4 Mathematically this is expressed as $RT = a + b * H$ where RT is the reaction time in seconds, H is the transmitted information, and b is an empirically derived slope. This linear relationship is known as "Hick - Hyman "Law" ".

conditions, the driving situation, and the illumination, ((Treiber & Kesting, 2013a),(Lindorfer, 2019),(Van Lint & Calvert, 2018)). In the literature body, such a process is modelled by using a Wiener process. This process adds noise in estimating variables of interest (gaps, relative speeds) but also accounts of a temporal auto-correlation in the noise term, leading to traffic instability.

2.2.6 Perception Thresholds

Naturally, humans respond to a stimulus when they perceive a change. This change and the extent of it is defined as the perceptual threshold. The model that contains such logic is one of Wiedemann. The perceptual constraints are expressed in terms of speed differences or space headway differences. A simulator study of (R. G. Hoogendoorn et al., 2011) showed asymmetry of the points of the reaction of the Wiedeman model and the drivers need larger Δv to react to the stimuli under adverse weather conditions. The later means that the perception threshold of the drivers became larger.

2.2.7 Spatial Anticipation

Spatial anticipation plays a significant role as a compensatory mechanism that reassures safe driving when the reaction time is higher than the time headway. By knowing the vehicles ahead and some times the vehicles succeeding the ego one, play a crucial role in collision-free driving, (Treiber & Kesting, 2013a). That is proven in the simulation study of (Treiber et al., 2006) when the traffic is more stable when considering five or more vehicles rather than only one downstream vehicle. This anticipation, if modelled properly, it is capable of showing stabilizing effects on traffic flow.

2.2.8 Temporal Anticipation

Like the spatial anticipation, there is the mechanism of temporal anticipation wherein drivers project their state couple of seconds in the future. This behaviour can be applied mathematically by assuming a constant-speed or constant-acceleration heuristic, (van Lint, Calvert, Schakel, Wang, & Verbraeck, 2017) to the modelling approach. Other authors, (Treiber et al., 2006), apprehend the role of anticipation, but when it comes to modelling, assume that a human driver can estimate their speed easier than acceleration. That said, they use only the constant-speed heuristic as it is more natural to humans. Generally, both spatial and temporal anticipation is considered of great importance to the role of traffic stability when reaction time increases,(Lindorfer, 2019).

2.2.9 Imperfect Driving

It is evident, not only from the literature body but from the experience when driving, that every driver has different capabilities. Another evidence that is usually traffic engineers runs into regularly, is the scatter plots of the fundamental diagrams. The sparsity of on the diagram declares, among other things, that the drivers are imperfect. This imperfection that related to errors and irregularities in driving, emerges as acceleration. The ways to models are two, either incorporate a white noise component at the equation of motion or include a correlated Wiener process. Needless to mention that the second method is preferred as the Wiener process encapsulates a sort of persistence, a phenomenon that actually exists in the real driving process. Nevertheless, in some studies, (Treiber & Kesting, 2013a) the process is simplified by including white noise. Either way, to represent the imperfect driving with a such modelling technique, is in the calibre of the researcher.

2.3 DRIVING BEHAVIORAL MODELS AND THEORIES

The section aims at presenting and understanding the theories and mental models that describe and explain the driver behaviour. We start by presenting the driving context of the driving process and see the various levels with the accompanying decisions that made at each level. We continue by elaborating on the human processing information models and the theory of Situation Awareness(SA), a rather fundamental mental model as it refers to those mechanisms which account for an operators awareness of their environment. Thereafter, the decision model of Fuller's is outlined.

2.3.1 The Driving context

(Michon, 1985) suggested that to understand human behaviour in the traffic context, must treat the problem from a broader perspective wherein the human is one of the many components. Having this as a reference point, he introduced four distinct levels that a human driver is in a perpetual interaction with the vehicle, the environment and the rest of the road users. The first level treats a human being as a user in the driving content, transportation consumes, an active social being and a psycho-biological organism satisfying their basic needs. Within this framework, he proposed a rudimentary, albeit generalized, problem-solving task of the road user which defines three hierarchical levels; the strategical, the tactical and the operational, (Michon, 1985). The

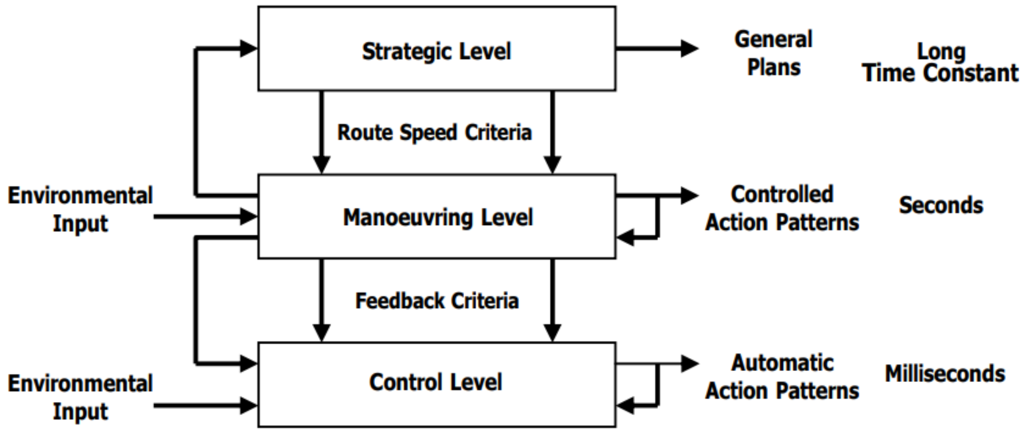


Figure 2.2: Generalized problem solving task of the road - user according to (Michon, 1985)

strategical level regards the planning stage of a trip, including the trip goals, the route, and the modal choice. Furthermore, the trade off between costs and risks is included at this first stage. The following (lower) level is the tactical or maneuvering. At this level, a driver exposed to controlled strategies limited by the real-time conditions on the road, obstacle avoidance, gap acceptance, turning and overtaking. At the lowest level, the control, drivers apply automatic responses such as pressing the pedals.
A similar approach proposed by (Rasmussen, 1983) for modelling the human behaviour. This approach regards the measurement of driver's performance as a function of consciousness under three distinct levels; knowledge-based, rule-based and skilled based. The broader level which is the knowledge based level is used when a road user deals with an unfamiliar situation on the road. In this situation, a road user defines a goal while analyzes their surroundings develops a plan to follow and attain the goal. Following that, the lower level, is the rule-based, wherein subroutines are deployed in a controlled way to deal with the situation. Lastly, the skilled based level pertains to behaviour that the goals achieved without any conscious control of the decisions. The reader immediately conceives that there are similarities between these two theories but there are differences as well.

In a nutshell, combining the task - hierarchy of Michon's, the task - performance of Rasmussen's and the basic understanding of the information processing strictly connected with the frameworks of (Shinar, 1978) and (Endsley, 1995), the outcome is a 3-dimensional conceptual construct illustrated in Figure 2.3. This illustration may be intuitive, but has a setback the substantial difficulty to model the interaction between the stages and the layers.

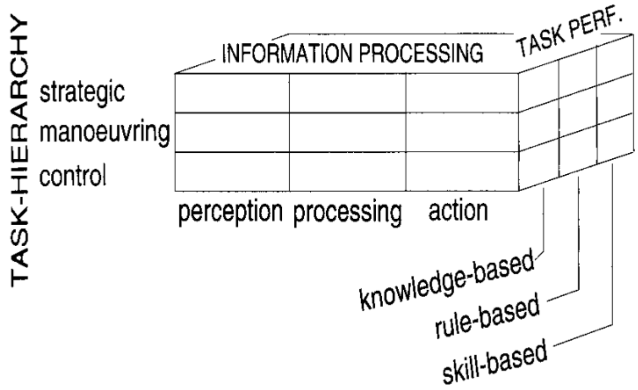


Figure 2.3: Driving tasks after (Theeuwes, 1993)

2.3.2 Human Processing Information Models

A fundamental model that provides a useful framework to analyse the different psychological processes is offered by (Wickens et al., 2015). This model is rather complicated to represent the driving behaviour as depicts details that are not in the interest of a traffic engineer yet. Nevertheless, it is an adequate base for understanding the process of thinking and what mental constructs involve, as it is illustrated in figure 2.4. The environment and its components are processed by the senses -vision, sound, touch e.t.c. - and maybe allocated to the short term sensory store. Next to it, is the perception which is responsible to determine the meanings of the sensory signal. This is realized with the aid of long-term memory as well. Following that is the response selection where a human triggers their response. The response execution, which is the last stage, demands the time of the signal which rooted in the brain, to reach the muscles responsible for realizing the response. The elements of feedback and attention are considered to be vital for the model as the fist updates the environmental changes to the rest elements and the second regards how much mental effort is needed to the perception process. Although this model has a fundamental use in the HIP, the model of Shinar's(Shinar, 1978) is considered to be more related and simplistic to understand the HIP in the driving domain.

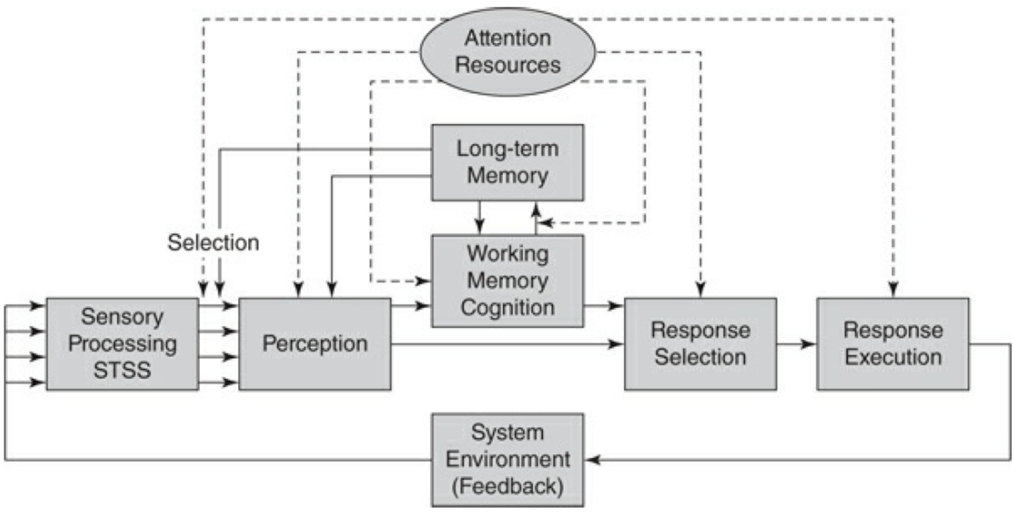


Figure 2.4: A model of Human Information Processing stages adapted by (Wickens et al., 2015)

In this framework, the main processes that encapsulate a human driver in the driving domain are shown in figure 2.5. According to the present model, a human driver is in contact with the external world through its sensory receptors, receiving raw information. The inputs from the visual proxy include other drivers, pedestrians, traffic signs and signals and displays on their vehicles, such as speedometer and the mirrors, (Shinar, 1978). There are inputs from the auditory proxy of a driver that is the sounds of the other vehicles, the present vehicle such as the acceleration and the deceleration sounds. All these stimuli are irrelevant with the driving task, but there are irrelevant stimuli such as the environment (weather), music on the radio, other co-passengers talking, navigation system and so forth. Perception is the process of interpreting and providing meaning to sensory data, (D'Addario, 2014). Related to the human driving, (Van Lint & Calvert, 2018) see this process in which the observed environment is recognized, understood and translated into stimuli, such as distance gaps and speed differences. Additionally, this process is subjected to the driver's characteristics and traits and the mechanical characteristics of the vehicle. The following step on this control-framed model is the response from the driver to the perceived stimuli. This process takes two steps. The first step is the selection of the appropriate response, while the second is the signal to be transmitted from the brain to the set of muscles to execute the response.

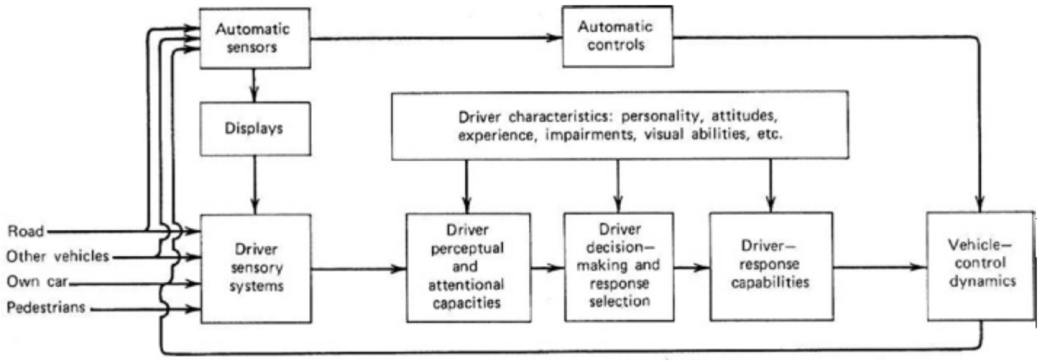


Figure 2.5: A model of Human Information Processing stages adapted by (Shinar, 1978) and slightly modified

Another crucial mental construct is the workload, which according to (Wickens et al., 2015) is the amount of information-processing resources used per time unit, to meet the level of performance required. Similar definition suggested by (De Waard, 1996), where the mental workload regards to the information processing demands imposed by the tasks that need to be executed. This construct connects the tasks and subsequently its requirements(demands) with the capability of a road user, (Theeuwes, 2017). Mental workload during driving emerges differently to novice and experienced drivers. For instance, for a new road user, even the primary tasks of lane-keeping, control of vehicles, speed control etc may substantially impact the road user. In contrast, experienced road users can perform all the primary tasks without any problem. In special circumstances, such as the adverse weather conditions, can increase the workload during the whole trip, (Theeuwes, 2017).

2.3.3 Endlsey's Situation Awareness mental model

A fundamental concept for dynamics systems which includes behavioural aspects is the situation awareness. According to (Endsley, 1995) Situation awareness is *The perception of the elements in the environment within a volume of time and space, the comprehension of their meanings, and the projection of their status in the near future*. Three levels involved in the concept of situation awareness; Level 1 - Perception of the elements in the environment, Level 2 - Comprehension of the current Situation, Level 3 - Projection of future status. The first level of SA is to perceive the status, attributes and dynamics of the elements in the environment. Related to the driving environment, this could be other vehicles, the infrastructure and possibly external conditions such as the weather. The following level of comprehension, includes the understanding of these elements based on the knowledge of level 1 while synthesizing patterns of other elements allowing the decision-maker to attain a holistic picture of the environment capable of knowing the significant objects and events. The last level is the projection of the current state, dynamics and elements into the near future. The projection may depend on the mental state of a driver and as well as their "level" of driving:novice, experienced.

2.3.4 Fuller's Decision Making Model

From human factors viewpoint, (Fuller, 2011) describes the driving task as a function of the perceptual processes and some (pre)-defined standards. Hence, the Task-Capability-Interface (TCI) was constructed as an effort to understand what incentives a driver in decision making with an emphasis on risk acceptance. In this model, task difficulty emerge from the dynamic interaction between the task demand and the drivers capability. Driver's task capability manifest from basic physiological characteristics, training, education and experience. Task demand arises out of large number of factors such as vehicle performance, route choice, physical characteristics of the environment and the traffic complexity on roads. The concept that introduced first and is a key hypothesis behind TCI model, is the *task difficulty homeostasis*, in which a driver tries to maintain the perceived difficulty of the driving task within acceptable levels. In order to do so, driver adjust their control variables, i.e. desired speed and headway. It is admitted that a frequent compensation action when raining or in the presence of fog is the reduction of the preferred speed for keeping the perceived risk at low levels, (Campbell & Stradling, 2003). Furthermore, it is argued by (Fuller, 2005) that apart from speed adaptation, a driver can regulate time headway in the case of car-following.

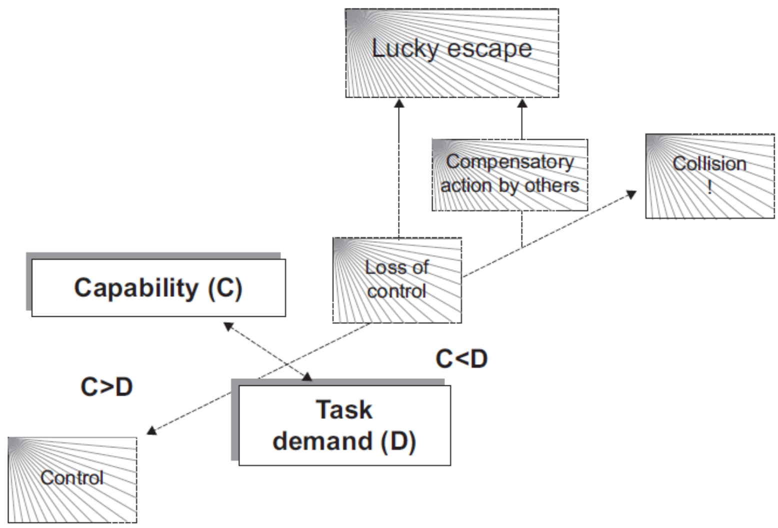


Figure 2.6: Task-Capacity-Interface model, (Fuller, 2005)

In Figure 2.6 it is an illustration of TCI as (Fuller, 2005) proposed. When driver's capability is larger than the task demand, the perceived task difficulty is lower than the acceptable limit, driver has the full control of the situation. In the case that perceived task difficulty is higher than the acceptable limit, a diver is likely to slow down by reducing this undesired task difficulty within acceptable limits.

The inclusion of Human Factors to a simulation logic of car-following models is well acknowledged by many researches (Saifuzzaman & Zheng, 2014),(Treiber & Kesting, 2013a), (Hamdar, Treiber, Mahmassani, & Kesting, 2008),(Van Lint & Calvert, 2018). There are two main psychological constructs that are defined in the HF literature which are exploited here. The first is the Situation Awareness SA as described in (Endsley, 1995) and adapted in the work of (Van Lint & Calvert, 2018) for describing the closed loop driving process of perception and response. The second concept is the Task Demand TD which is used in explaining the driving deterioration performance. The TD is define as the demands of the process of achieving a specific measurable goal using a prescribed method,(Cacciabue & Carsten, 2010).

Two main dimensions of human factors modelling in traffic are considered in the present study. The first is the *perception* of the environment and the second is the *response* to the stimuli. In the driving task, the stimuli are the distance gaps, and the speed differences. This process is bounded by any individual driver and its traits; attributes, skills, current mental state and the mechanical characteristics of a given vehicle. The response process is based on the perceived stimuli.

2.4 CONCLUSIONS OF THE LITERATURE REVIEW

In the first section of the literature review, a thorough discussion of the adverse weather conditions is made. The author pointed out definitions on the of what we consider normal conditions and what are the predominant weather events that emerge frequently on the road traffic systems. At a collective level, the results of the inclement weather can be seen from the capacity and the speed of a road system. At an individual level, the discussion focus on studies that make use of simulator while the effects on the drivers' behaviours translated to time or space headways. From the perspective of safety, a usual measure is a time-to-collision to assess the impact of the weather on safety. The weather events that reviewed in the literature are two the fog and the rain. That is not by accident as the first pose difficulty on the perception of the human driver while the second gives an additional difficulty to the longitudinal driving by degrading the friction.

In the second section, the human factors that included the microscopic models are discussed. The models of human information processing are elaborated. The more relevant model is considered the one of (Shinar, 1978) as was developed tailor-made to the driving context. Then, all the relevant human factors are well discussed. Some of the human factors are elaborated more as more studies can found in the literature.

The third section of the literature is an aim to assess behavioural theories in the context of driving. The examination of the theories start from a board perspective, (Michon, 1985), and how the problem of traffic must be treated. A hierarchical level of the traffic is elaborated the on of (Michon, 1985) while additional knowledge offers the behavioural theories of (Rasmussen, 1983) which is very similar to the first one. The section concludes with the explanation of the mental construct of the situation awareness, a well-studied and developed construct given by (Endsley, 1995) and used to understand the awareness state of a human being.

At this point, the following sub-questions are answered:

- Which is the phenomena that affect the normal traffic conditions and how they emerge to an aggregate level?

  The weather events that affect the normal road traffic operations are the rain, the fog, the snowfall windstorms and low/high temperatures. The most frequent and studied events are the first three.

- To what extent these phenomena affect the traffic supply?

  To answer adequately this question we have to consider that is subjected mainly to two parameters. The first is the intensity of the weather phenomenon and the second is the country that the study is carried out. The precipitation intensity has different categorization over the reviewed literature. Overall, the most common categorization is nominal, namely light, moderate and high intensity. The second parameter is the case study. As we suspect, the driving style of the road users, the experience many other traits of the users, at the end reflected on the performance of the driving. Bearing these parameters in mind, for the phenomenon of rain, the degradation of the performance of the drivers in terms of speed starts from 2% and can reach to the extreme of 13%. The capacity under rainy impended from 1% to 21%. Most of the studies conducted were data-driven approaches except for one study that was made in a simulator. The results are in good agreement with those of real data. Under snowy conditions, the impacts of the weather were larger than those of rainy conditions. The mean speed suffered from 3 to 45.4% reductions. In the empirical studies, the extreme value of the mean speed was 15.6%. The extreme value of 45.6% was a derivative of a driving simulator which is a matter of question this result. The capacity was hindered between the values of 4% to 27.82% and again, an extreme value of 67.6% was yielded from a traffic simulator. When the visibility of the drivers affected the deterioration of the mean speed is 7% to 12% for the empirical data and 4% to 32.8% for data derived from a traffic simulator. The capacity for both cases degraded 10% to 12.5% for both cases.

- What weather phenomena can be incorporated into a simulation?

  According to the present literature, the weather events that are most studied are the rain, the snow and the fog. Because the first two events have similarities concerning the effects that pose to the driving environment and the road - user, it is preferred from the author to include the events of rain and fog in the analysis. The fog, as we admitted above, affects only the visual sensory receptor of the driver while does not affect at all the vehicle. This event is a good starting point to think that this phenomenon influences the human behaviour of the driver and include it to the framework as a parameter that increases the task demand when a driver performs the task of car following. For the rain, it can be said that the rain has an additional impact on the performance of the vehicle per se. That is happening due to the degraded friction factor between the vehicle's wheels and the road surface. To expand a little further, when a driver does receive stimuli, comprehend it and decide for their response, it would not be perfect due to this degradation we mentioned above.

- How the inclement weather affects human behaviour?

  When reviewing the longitudinal motion of the vehicles, for the weather events of fog and rain, it was found that the so-called human behaviour is seen as the result of the decision of the road-user on time headway and the preferred speed. In the weather event of fog, in some studies, the time headway is increasing as a compensatory mechanism to reduce the potential risk, and in some other studies, it was found that the drivers follow their leader regardless the reduced visibility. This tailgating was observed most likely as the drivers wanted to be aware of the situation downstream, rather than slowing down and lose their visual contact with their leader. Nevertheless, in some simulator studies the participants constructed in doing so. In the event of the rain, similar individual behaviour was observed.

3 MODELLING VEHICLE KINEMATICS AND HUMAN FACTOR

The previous chapter gave us the knowledge to understand the complex phenomenon of driving under adverse weather conditions. In this chapter, the methodology is illustrated. Firstly, we elaborate on the components that constitute a vehicle's movement. A vehicle obeys a longitudinal model of movement. We choose to experiment with the IDM+ model for reasons that we discuss in the running text below. The original formulation of the model does not account for any external environmental condition. To overcome this drawback, a formulation is proposed to the acceleration and the deceleration parameters based on the physics and the available literature. Accordingly, the acceleration (deceleration) parameters are governed by equations that introduce the dynamic characteristics of the vehicle. Some new parameters are introduced to the formulation. To keep the model in its simplest form, we choose to include only a necessary number of new parameters. To the acceleration function, rolling coefficients, the mass on the tractive axle and the friction between the tire and the road surface are the new parameters. We see that the vehicle's mass on the tractive axle is of great importance parameter as defines the acceleration rate of a vehicle. The breaking function introduces the braking efficiency, the friction coefficient and the rain intensity. To expand our understanding, we perform a simple simulation of a car following in MatLab. The factors that are perturbed in this simulation is the friction coefficient and the rain intensity. To do so, the correct method of sensitivity analysis must be used. The decision is taken depending on the model that we use. As the car-following model is not obeying to any linear relationship, a Global Sensitivity analysis is applied with the use of Latin Hypercube Sampling technique.

Secondly, the *human factor* framework is discussed according to (Van Lint & Calvert, 2018), elaborating on the mental constructs which includes. The main concept behind the framework is that the process of driving is addressed as a dual interconnected loop of perception and response. The mental model of Situation Awareness accounts for the perception state of the drivers. It is assumed that the higher the awareness state, the fewer perception biases suffer the drivers. The second mental model that constitutes the framework is Fuller's TCI. This mental model explains the driver's motivation (why) to adapt their speed and/or headways as a function of their perceived risk, which in the framework emerge as the state parameter of Task Demand. The motivation of such adaptations yields from a comparison mechanism between the task capacity and demand.

Thirdly, the briefly described framework forms a basis to incorporate "new" mechanisms that permit us to explain and generate in a simulation experiment the traffic flow characteristics under foggy and rainy conditions. In section 3.2.2 the extended framework of rain is illustrated. In section 3.2.8, the extended framework of fog is illustrated.

Lastly, conclusions are drawn related to the proposed model that governs the vehicle dynamics and the human behaviour.

3.1 VEHICLE

Vehicle longitudinal dynamics are represented by the so-called microscopic models. A well studied mathematical model in microsimulations is the IDM. The IDM model falls into the class of the deterministic stimulus-response models having the following advantages as (Treiber, Hennecke, & Helbing, 2000) postulate; (i) it behaves collision-free due to its dependency on the relative speed, (ii) it has self-organized characteristic traffic constants demanded, hysteresis effects and complex states, (iii) all the parameters have reasonable interpretation, measurable, and have the expected order of magnitude, (iv) calibration is possible, (v) low computational burden. As (van Wageningen-Kessels, Van Lint, Vuik, & Hoogendoorn, 2015) state, the stimulus-response models assume that drivers accelerate(decelerate) in response to the stimuli of (i) own current velocity, (ii) spacing w.r.t. leader, and relative velocity w.r.t. leader. The mathematical formulation of a vehicle acceleration that (Treiber et al., 2000) proposed is the following:

$$\dot{v}_n = \alpha^{(n)} \left[1 - \left(\frac{v_n}{v_0^n} \right)^{\delta} - \left(\frac{s^*(v_n, \Delta v_n)}{s_\alpha} \right)^2 \right] \tag{3.1}$$

where α is a combination of vehicles maximum acceleration and preferred human acceleration, v_0 is the desired speed when driving in the free-flow regime, and δ is a factor that defines the rate of a drivers when approaching from their current speed to the desired speed. The function 3.1 calculates the acceleration of the subject vehicle by interpolating between the free-flow regime and the interaction regime. The free-flow regime is expressed with $\alpha^{(n)} * (1 - (v_n/v_0^n)^{\delta}$ while the interaction regime is expressed with $-\alpha^{(n)} * (s^*(v_n, \Delta v_n)/s_\alpha)^2$ term. The interaction terms is a function of the current space gap and the desired minimum gap which is expressed with the following equation:

$$s^*(v, \Delta v) = s_0 + v_n T + \frac{v_n \Delta v_n}{2\sqrt{\alpha b}} \tag{3.2}$$

where s_0 is the stopping distance when the cars coming at a standstill position, T is the time gap b is the maximum comfortable deceleration.
Despite the completeness of the proposed car-following model, some deficiencies pointed out by (Schakel, Van Arem, & Netten, 2010) specifically the unrealistic capacity values. Owning to this impairment of the original formulation, the same authors applied a minimization over the free-flow and the interaction term given by the following equation:

$$\dot{v}_n = \alpha^{(n)} \min \left[1 - \left(\frac{v_n}{v_0^n} \right)^{\delta}, 1 - \left(\frac{s^*(v_n, \Delta v_n)}{s_\alpha} \right)^2 \right] \tag{3.3}$$

The new equation 3.3 was named IDM+ to be distinct from the original formulation of IDM. Apart from the observed capacity changes, the shape of the fundamental diagram changes as well, from a smooth topped-off to a triangular. The improvements as they have seen in the research is the minimum number of the parameters which implemented to the model. These parameters have either an intuitive or physical meaning. Nevertheless, there is a drawback concerning the calibrated model to the congested conditions. In this situation, the fit in congestion is problematic due to the dependency on the stochastic input. The typical values for the parameters of IDM+ are concentrated subsequently. The desired speed of v_0 is set 30m/s. The time gap is 1.5s and the stopping distance s_0 is 2.0m. The desired acceleration a has the value $1.4m/s^2$, while the comfortable deceleration b is $2.0m/s^2$. Nevertheless, the values of the parameters are substantially differed over the case studies depending on the knowledge of the prevailing circumstances every time.

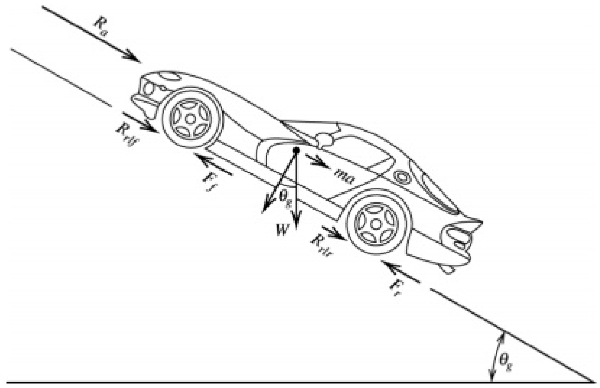
Despite that the former mathematical formulation is such to represent the dynamic interaction with other vehicles adequately, it does not reflect the interaction conditions between the tires and the road surface. To do so, first, we illustrate the basic vehicle dynamics and consequently, a mathematical formulation is proposed to account for the surface conditions affected by weather events. In figure 3.1 we see all the forces that are posed on a moving vehicle. In general, two forces are posed to a moving vehicle, the tractive effort and the resistance. Tractive effort is the available force to perform work to a vehicle and make it move. Resistance is the force that acting to the opposite direction of a moving vehicle hindering its movement. There are three sources associated with the resistance; the aerodynamic resistance (R_a), the rolling resistance (R_r) and the grade resistance (R_g).

By summing all the forces on the traversing axis the following equation provided:

$$F_f + F_r = m * a + R_a + R_r lf + R_r lr + R_g \tag{3.4}$$

The tractive effort of a vehicle depending of the engine power P[kW], the traversing speed v[m/s] and the transmission efficiency η[unitless] is calculated by the following equation:

$$F_t = 3600 * \eta * \frac{P}{u} \tag{3.5}$$



R_a = aerodynamic resistance in lb,
R_{rlf} = rolling resistance of the front tires in lb,
R_{rlr} = rolling resistance of the rear tires in lb,
F_f = available tractive effort of the front tires in lb,
F_r = available tractive effort of the rear tires in lb,
W = total vehicle weight in lb,
θ_g = angle of the grade in degrees,
m = vehicle mass in slugs, and
a = acceleration in ft/s^2.

Figure 3.1: Adapted from (Mannering & Washburn, 2020), illustrating the forces on a moving vehicle

Accordingly, the maximum tractive effort is computed with the following equation,accounting for the friction coefficient.

$$F_{max} = g * m_{ta} * \mu \tag{3.6}$$

where m_{ta}[kg] is the mass of the vehicle on the tractive axle, μ is the friction coefficient and g[m/s^2] is the gravitational acceleration. To ensure that the force is not infinite when the vehicles moving with low speeds, the use of the following equation is suggested.

$$F_f = min(F_t, F_{max}) \tag{3.7}$$

Before continuing, it is crucial to recall under which circumstances the research is performed. The research includes the friction coefficient while deliberately omits any inclination or wind resistance as the additional parameters will over-complicate the study. This study aims to promote a generic conceptual framework that sets at the forefront the cognitive mechanisms as a possible explanation of the driving behaviour under inclement weather. That said, the resistance due to grade and the aerodynamic resistance is excluded from the formulation. For those who want to get more insights into the dynamics of the vehicles, both longitudinal and latitudinal, the following literature is proposed (Mannering & Washburn, 2020) or (Rajamani, 2011).
When considering rolling resistance, three sources are worth highlighting. The first is the stiffness of the tire and the road surface. This interaction between the surfaces affects the magnitude of the penetration, the compression and the tire deformation. The wet surface conditions impose lower rolling resistance The second source, include the physical characteristics of the tires per se. That is the pressure and the temperature of the tire. Depending on the different varieties of these two parameters the tire can have increased or decreased rolling resistances and different shapes of deformations as well. The last source is the vehicle's operational speed. The speed affects the deformation of the tire and causes vibrations and flexing to the tires which lead to higher rolling resistance. A well-used formulation for the rolling resistance according to (Mannering & Washburn, 2020) is the following:

$$R_rl = f_rl * W \tag{3.8}$$

Where the f_rl is a unitless coefficient that considers only the vehicle's speed. That said, this formulation is not capturing any friction between the tires and the road surface. Also, this model does not account for any wet conditions or the deformation of the tire. To overcome the bottleneck that the original formulation has, a model proposed by (Rakha, Lucic, Demarchi, Setti, & Aerde, 2001) is used in the study, including parameters such as the rolling coefficient C_r as a function of the road surface and condition of the road, rolling resistance coefficient (c2,c3) that represents the tire types(bias ply and radial) and the mass of the vehicle. The mathematical formulation is as follows:

$$R_r = g * C_r * (c_2 * u + c_3) * \frac{m}{1000} \tag{3.9}$$

Despite that the original formulation of the equation 3.8 had been developed for heavy trucks, it has proven that performs adequately for conventional vehicles as one can see in the studies of (Rakha et al., 2010), (Rakha, Arafeh, & Park, 2012), and (Rakha, Snare, & Dion, 2004).

$$a_{max} = \frac{F_f - R_r}{m}; \tag{3.10}$$

To account for the maximum deceleration under inclement weather a formulation by (Rakha et al., 2001) has been proposed and have already used in various simulation suites (Rakha et al., 2010). Even if the formulation of the maximum deceleration is empirical, it obeys the mathematical formulation proposed by (Mannering & Washburn, 2020) while includes parameters such as the rain intensity, the friction coefficient and the braking efficiency which is a unitless factor reflecting the degree of the braking system that is below the optimal state. To that end, the are two proposed equations:

$$b_{max} = (0.5088 - 0.03948 * RI) * g = \eta_b * \mu * g * (1.0 - 0.07759 * RI) \tag{3.11}$$

In the equation 3.11, the RI stands for the rain intensity, the g is the gravitational acceleration, the μ is the friction coefficient and the η_b is the breaking efficiency. Note that this relationships are empirical and the maximum rain intensity that is modelled is up to 7cm/h. The coefficient of breaking efficiency for the rest of the analyses will be set to one. Than means that the technology of the vehicle make use to the greatest extent the breaking capacity of the vehicles. The equation 3.10 can be applied to the original formulation of the IDM+ model and account for the surface conditions. The original formulation of the IDM+ can be rewritten as follows:

$$\dot{v}_n = \left(\frac{F_f - R_r}{m}\right) * \min\left[1 - \left(\frac{v_n}{v_0^n}\right)^{\delta}, 1 - \left(\frac{s^*(v_n, \Delta v_n)}{s_\alpha}\right)^2\right] \tag{3.12}$$

and the desire headway transformed into:

$$s^*(v, \Delta v) = s_0 + v_n T + \frac{v_n \Delta v_n}{2\sqrt{\left(\frac{F_f - R_r}{m}\right) * b_{comf}}} \tag{3.13}$$

It is clear here that we violate the use of the term maximum acceleration of the original formulation by including the mechanical characteristics of the vehicles. To include, as simple as possible, the human influence on the acceleration, it is proposed to incorporate a term of behavioural acceleration a_{beh} which reflects the preference of the drivers towards the desired acceleration. In this way, we dissect what the performance of a vehicle is and what the reference of a human driver is. To expand further, mathematically we simply use a minimization term between mechanical acceleration and behavioural acceleration and thus is expressed in the following manner:

$$a = min(a_m, a_b) \tag{3.14}$$

where $a_m = (\frac{F_f - R_r}{m})$ and $a_b = 3m/s^2$. It is evident that the value of the behavioural acceleration is selected arbitrary, but not that arbitrary enough to make the kinematics to generate irrational output. Then, the equation 3.14 is plugged in to the equation labeleq:12 to finally derive the acceleration of vehicle. To the other end, the maximum deceleration is limited to:

$$\dot{v}_{n,dec}^{max} = max(-\dot{v}_n, -b_{max}) \tag{3.15}$$

The equation 3.15 is established in order to account the impact of the degraded surface conditions on the deceleration performance of the vehicle. The modification of the IDM+ apart from the road surface characteristics includes additional vehicle characteristics as well. The next step is to set baseline values to the parameters of the model in order to get realistic kinematic behaviour of the model. The values of the parameters are included to Table 2.3 at the Appendix B.

3.1.1 Sensitivity analysis on the proposed formulation

For a more intuitive understanding of the mathematical formulation that proposed above, a simulation was devised in MatLab of a leading and a following vehicle. In this simulation we use the equations 3.13, 3.16. The leading vehicle has at t = 0s and x = 0m an initial speed of 20 m/s. After 1s the leader is decelerating with a rate of $3m/s^2$ for the next 1s. At t = 2s, the vehicle accelerating with a rate $3m/s^2$ for another 1s. After that, the leader continues its course with constant speed at 20 m/s. At t=0, a following vehicle with an initial speed of 22

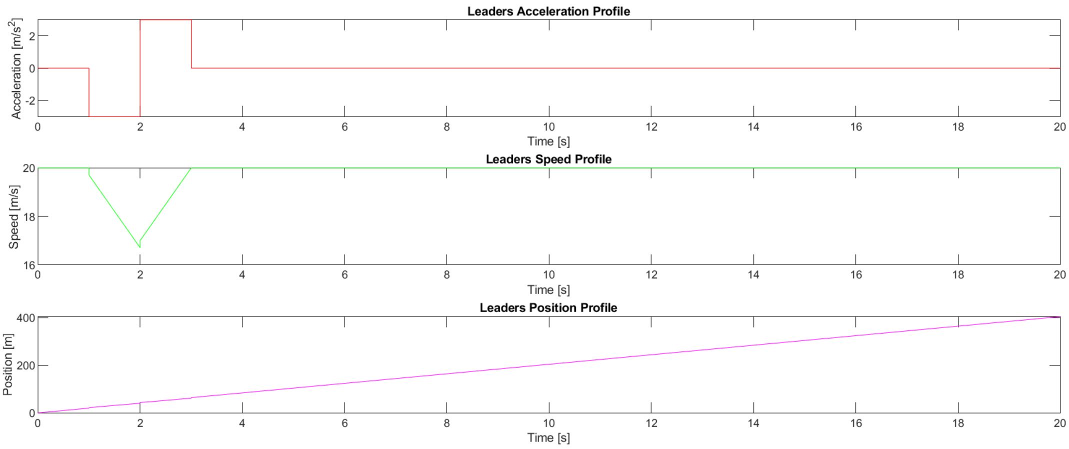


Figure 3.2: Leading vehicle acceleration, speed, and position profile

m/s, is moving at a distance 50m back from the leader. The parameters that perturbed are the friction coefficient and the rain intensity. The rest parameters introduced in the formulation remain constant. The values of the parameters are amassed in the Table 2.3. A method to assess the impact of the input parameters to the response of the model is to perform a sensitivity analysis. As we mentioned above the Latin Hypercube Sampling (LHS) is used. The manner that the sampling technique works , is not described here but is briefly discussed in the Appendix A. We choose to set, as input parameters, the friction coefficient and the rain intensity to follow, respectively, a uniform distribution with the following specifications:

$$\mu \sim Unif(mu_{min}, mu_{max}), ri \sim Unif(ri_{min}, ri_{max}), m_{pta} \sim Unif(m_{pta}min, m_{pta}max) \tag{3.16}$$

The friction coefficient is bounded within the values of 0.4 and 0.65 and the rain intensity within the values 0 and 30 mm/h. The percentage of the mass on tractive axle is limited to 0.45 and 0.60. By creating a two dimensional space of values, we sample the parameters 500 times. The results of the sampling is shown in the Figure 3.3.
Before doing the simulation, we propose measures of performance (response parameters) while hypotheses formed to assess the findings statistically. As the experiment is carried out at a disaggregate level, the response parameters would be the speed, the acceleration and the desired headway of the following vehicle. The author chooses to obtain the mean value of the speed, acceleration and desired headway over all the input parameters variations. Someone can argue that the maximum or minimum value could have captured the vehicle's behaviour at the same degree as the mean value. Nevertheless, we choose to obtain the mean values as a stronger statistical measure than obtaining only a single value of each permutation. The following hypotheses are structured to assess the findings of the simulation statistically:

H0 - 1: The friction coefficient does not affect the speed, the acceleration and the desired headway of the following vehicle.

H0 - 2: The rain intensity does not affect the speed, the acceleration and the desired headway of the following vehicle.

H0 - 3: The percentage of mass on tractive axle does not affect the speed, the acceleration and the desired headway of the following vehicle.

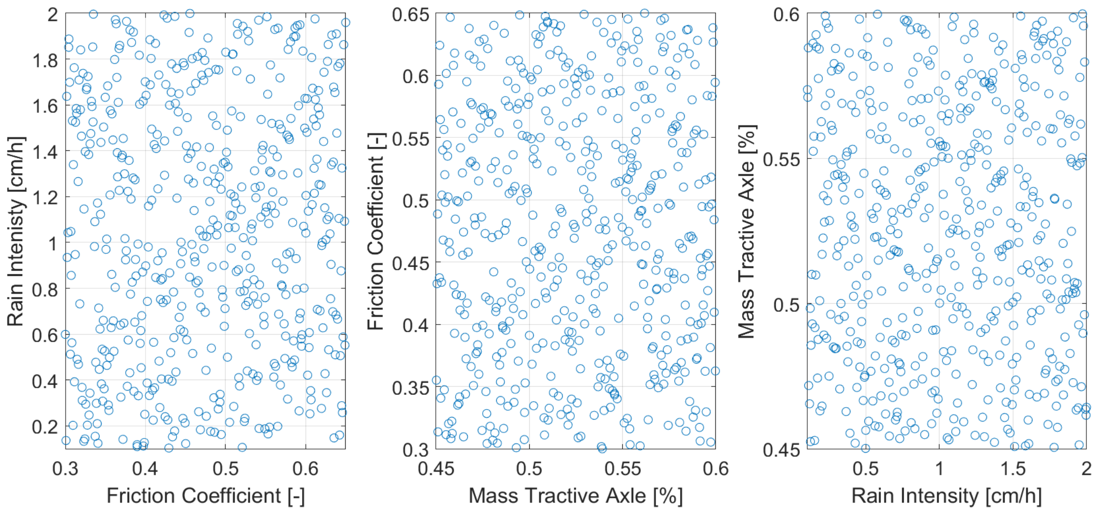


Figure 3.3: LHS sampling

We use the *Partial Rank Coefficient Correlation* (PRCC) due to the non-linear, although monotonic, relationships of the parameters. PRCC is a statistical measure that accounts for the non-linear associations between the input and the response parameters while correcting for any effects by other parameters on the response. This measure of performance is correlating the rank-transformed data by using linear regression models. According to (Marino et al., 2008), PRCC is a robust measure of sensitivity for non-linear and monotonic relationships between the input and an output parameter, given that the correlation between the inputs is little. As we are not aware of the correlation between the friction coefficient and the rain intensity, it is assumed that there is no correlation.

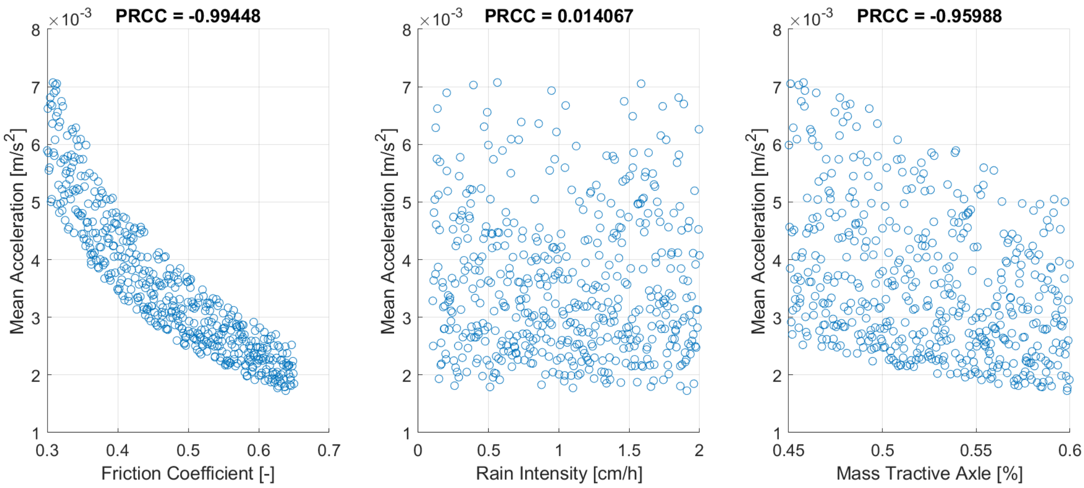


Figure 3.4: PRCC for the two input parameters and the mean acceleration of the 1st vehicle

In Figure 3.4 we see the PRCC of the three input parameters and the response parameter of acceleration. A strong negative relationship between the friction coefficient and the mean acceleration exists. On the other hand, there is no relationship between rain intensity and mean acceleration. The hypothesis we made about no relationship does stand. The mass in tractive axle has also correlation with the mean acceleration. The relationship is negative, which means that the more mass concentrated on the tractive axle the better acceleration response of the vehicle.

In Figure 3.5 we obtain the results for the desired speed response parameter. As we see, the changes on

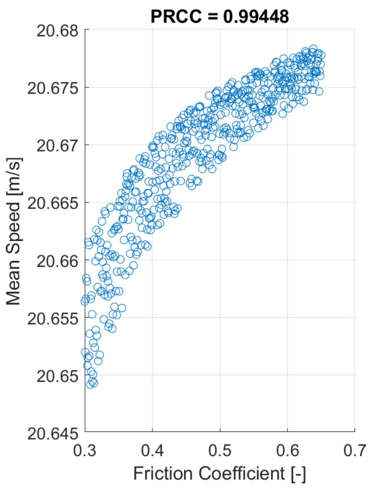


Figure 3.5: PRCC for the two input parameters and the mean speed of the 1st vehicle

the desired speed are subtle but still, the indicators of correlation reveal positive relationship between friction coefficient, mass on tractive axle an the mean speed. In both cases, the higher the friction coefficient (accordingly mass on tractive axle), the higher the desired speed. For the value of rain intensity, there is no relationship with the response parameter of mean speed.

The most interesting insight is illustrated in Figure 3.6 as a strong negative correlation founded for the friction coefficient and the mean desired headway. This result is intuitive and suggested in a large strand of scientific literature. The less the friction, the larger the desired headway of the drivers. There is an allegation in the scientific literature that the drivers opt for higher headways as a compensation mechanism. Accordingly, the rain intensity has a subtle correlation with the desired headway. Lastly, a strong negative correlation between mass on tractive axle and mean desired headway is shown. Intuitively, the less mass on vehicle's tractive axle, makes it rigid.

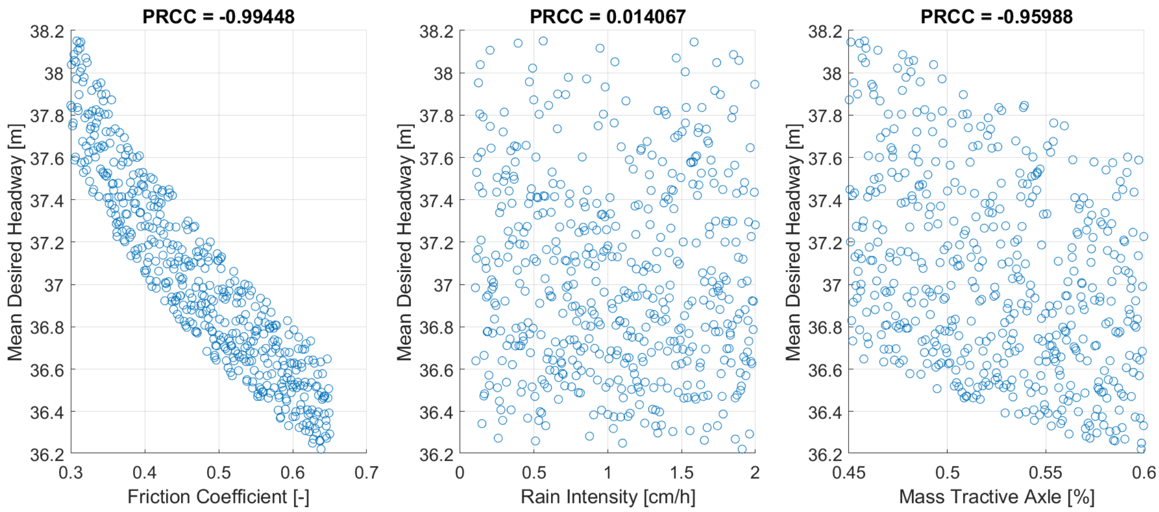


Figure 3.6: PRCC for the two input parameters and the mean desired headway of the 1st vehicle

By setting the mass of the vehicle to 1400 [kg], the rain intensity 1.5 [cm/h], the friction coefficient varying between 0.3 to 0.65 and the percentage of mass on the tractive axle is set to 0.55, we obtain the following response of the model.

What we observe on the response parameters of the model when perturb only the friction coefficient is that the maximum acceleration of the model drops when the friction is lower. The speed follows the same trend as the acceleration, while the desired headway increased when the friction coefficient has small value.

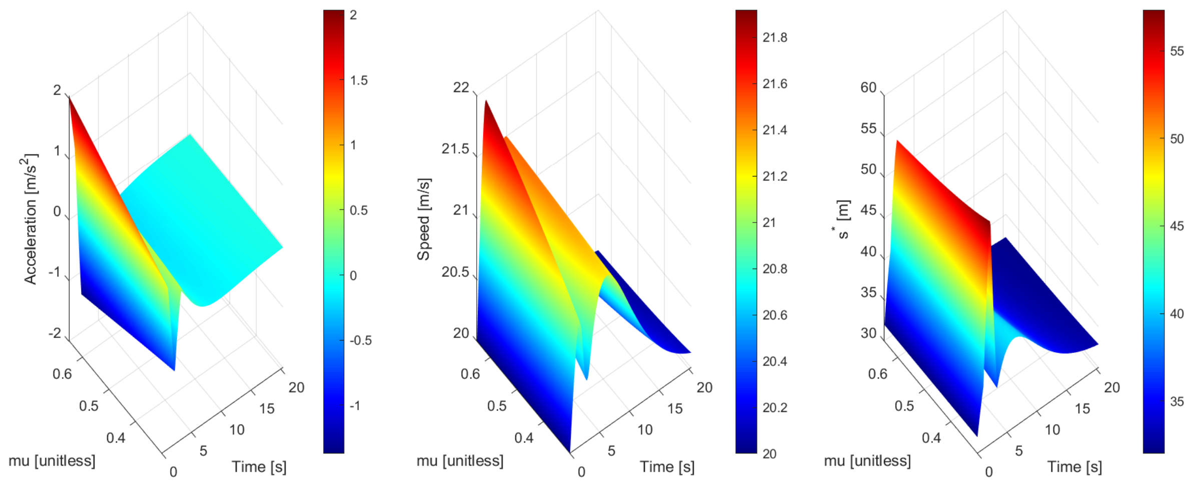


Figure 3.7: Response of the output parameters of the simulation for all the combinations of input parameters

Lastly, a boarder understanding of friction coefficient on the response parameters is obtained when looking at Figure 3.7. In this 3d diagram, we see clear relationships between the outputs.

3.1.2 Sub - conclusions

This section proposes an adaptation to the IDM+ including additional parameters that dynamically compute the acceleration and the deceleration a vehicle. The acceleration parameter is governed by the mass of a vehicle on the tractive axle, the friction coefficient, two rolling coefficients, one for the stiffness of the tire and the one for the geometric characteristic of the vehicle. The rolling coefficient is obtained from the literature supported by empirical evidence. The deceleration parameter was simpler in its formulation as includes parameters of the braking efficiency, the friction coefficient and the rain intensity. The mathematical formulation was based on a derivation after calibration with real data. With this derivation, the parameters of acceleration and deceleration of the original IDM+ model substituted forming the equation 3.13 and 3.16. The behaviour of the model was validated in Matlab. The results lead us to the following conclusions at a disaggregated level:

- The mathematical formulation is simple and the parameters are intuitive having a physical interpretation.
- The extension of the IDM+ seems to be effective to account for the environmental conditions of wet surface.
- No irrational values of the output parameters was found.
- The output values of the parameters are within the acceptable boundaries.
- The rain intensity does not exert any impact on the model.
- A positive association between the friction coefficient and the speed was found while negative with the acceleration and the desired headway.
- A positive association between the rain intensity and the acceleration and the mean desired headway was found while negative with the speed.

Some implications about the traffic at an aggregate level.

- It is suspected that at an aggregate level the performance of the traffic will be affected negatively, as the performance of the vehicles reduced.

- The safety performance of the traffic will be affected. This indication is derived by the degraded acceleration/deceleration performance.
- The travel time of the traffic is expected to increase as the mean speed is decreasing, and the acceleration response is low.

3.2 HUMAN DRIVER

This section aims to elaborate on the multilevel framework as first proposed in the study of (Van Lint & Calvert, 2018) for endogenously incorporating the HF. Subsequently, the same framework formed the basis of the studies of (S. C. Calvert, Schakel, & van Lint, 2020) and (S. Calvert, van Arem, & van Lint, 2020) for further investigating additional HF, such as the concept of the anticipation reliance and HF with automated vehicles to assess critical safe situations.

3.2.1 Basis

In the literature, we have discussed two mental models that reflect two human driver processes; perception and response. The mental models that are related with these two human processes are Endsley's Situation Awareness and the Fuller's Task Capacity Interface (TCI). TCI is based in the assumption that a loss of control is occured when the demands of the driving tasks exceed the capability of the driver. SA is connected with the knowledge of the state of a situation and the errors on a the control variables when SA is reduced. In other words, the Situation Awareness SA(t) encapsulates a driver's magnitude of awareness of their environment, while the TCI through the Task Demand TD(t) explains the driving performance. Of course there are other determinants that define the driver performance such as fatigue, drowsiness, drugs, distractions, emotions, level of effort etc, but here are not accounted in the model. The TD(t) can be seen as the cumulative workload of each cognitive task. The framework that we are using, describes the driving process in a way that:

(i) it is sufficiently accurate in order to derive sensible conclusions about the efficiency and safety of the traffic operations

(ii) is sufficiently generic, so as to append more human processes in the framework, by extending it or enriching it

(iii) it is sufficiently simple, both mathematically and computationally, in order to simulate large networks. By following those guidelines, the net result of the simulations describes how much mental effort drivers consume for a given task(s) and how that process affects the driving behaviour.

In order to keep the same streamline with the original work of (Van Lint & Calvert, 2018), we adapt the nomenclature for avoiding any confusion. Therefore the processes of perception and response formed with the following manner:

$$R_i(t + \tau_i(t)) = F(s_i(t), \theta_i(t), \omega_i(t)) \tag{3.17}$$

wherein $R_i(t)$ denotes the response of a driver i at the time instant t(the acceleration $a_i(t)$ in this thesis); $\tau_i(t)$ is the reaction time; $s_i(t)$ is the important stimuli from the environment; $\theta_i(t)$ is the driver's preferences i.e. desired speed and headway; $\omega_i(t)$ the set of the characteristics of the environment that may affect the response.

Furthermore, literature distinguishes two approaches to model the HF. The first approach is exogenous, by varying the parameters of a given model and endogenously, employing the framework that we discuss in the present chapter in a form of mental models and functions. The first approach has been seen in the work of (Treiber et al., 2000), (Lindorfer, 2019) and accounts for changing the parameters of models by varying the parameters(e.g. reaction time) either in a deterministic (e.g. fixed value) or a stochastic (e.g. drawn by a distribution) manner. The same studies provide an approach to incorporate perception errors by using a Weiner process. Besides, assumptions can be made to incorporate anticipation in the models; the most commonly used heuristic technique is constant-speed or constant-acceleration. The second approach of incorporating human factors overcomes the aforementioned drawbacks by introducing state variable and mechanisms (TCI, SA) in which the changes in perception and/or response is a dynamic function of their state, the stimuli and the environment. Some good examples are the prospect theory mechanism ((Hamdar et al., 2008), (Hamdar et al., 2016)) and the TCI model((R. Hoogendoorn, van Arem, Hoogendoorn, & Brookhuis, 2013),(Saifuzzaman & Zheng, 2014),(Saifuzzaman et al., 2017), (Kondyli, Chrysikou, Ramey, & Kummetha, 2018)).

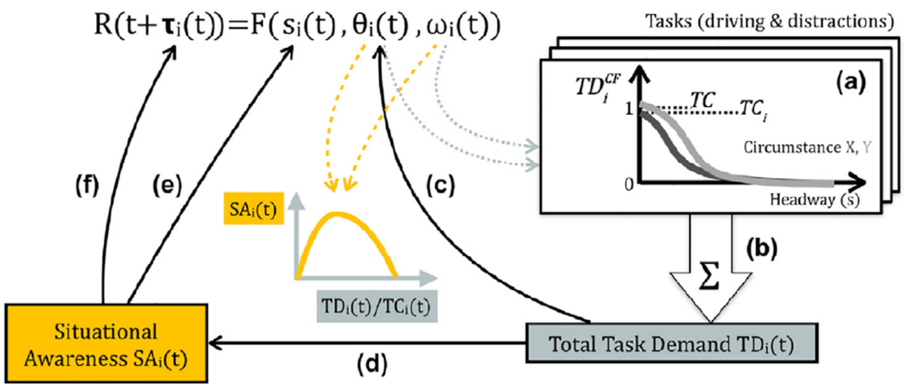


Figure 3.8: Original Conceptual framework as derived in the work of (Van Lint & Calvert, 2018)

The mental models of SA and the TCI are combined with the general equation of response 3.17 resulting in the framework that it is illustrated in figure 3.8. This figure illustrates the interactions between the mental models at the lower level and the collision-free car following logic at the upper level as a combined mechanism. There are six important points of the framework.

- (a) The so-called Fundamental Diagrams of Task Demand.
- (b) The task aggregation.
- (c) The effects of the total task demand on the preferences of a driver $\theta_i(t)$.
- (d) The perception state of a driver expressed by the mental model of Situation Awareness which in turn affects (assumed) the
- (e) perceived stimuli (space headways and relative speeds)
- (f) reaction time of each driver.

The grey dashed arrows point towards the TD(s), reveal that the traits and the environment define the TD and the capability of a driver. The TD of the car following sub-task is a function of the headway from the leading vehicle. The enlarged arrow pointing towards the Total Task Demand(TTD) assumes that the TTD is a summation of the sub-tasks. Following that, two black arrows pointing towards the traits(preferences in our case) of a driver, named (c) and the second arrow towards the SA, named (d). The TTD translated into TS affects the awareness of a driver. The SA is a function of TS, the driver's traits and the environmental conditions. Lastly, SA affects the perception by exerting errors (e) to the stimuli, and exacerbates the reaction time of the drivers (f).

A crucial component of the multilevel framework is the so-called Fundamental Diagrams of Task Demand (FDTD) and their meaning in the simulation context. According to the authors (Van Lint & Calvert, 2018), the FDTD must meet the following requirements:

- **Req. 1.** The Task Demand is formulated in units of "nominal" task capacity.

- **Req. 2.** Task Demand is expressed as a function of parameters that are available in the simulation. The main sub-task here is the car-following which its demand is expressed as a function of the time headway. The weather conditions are not deemed as secondary tasks, on the contrary, are hindrances to the environment-induced to the primary task(car-following). In other words, (R. G. Hoogendoorn, 2012), (Fuller, 2005) assume that the task demands are increased due to the weather conditions.

- **Req. 3.** The FDTD's at a tactical level is always prevailing to those of operational level.

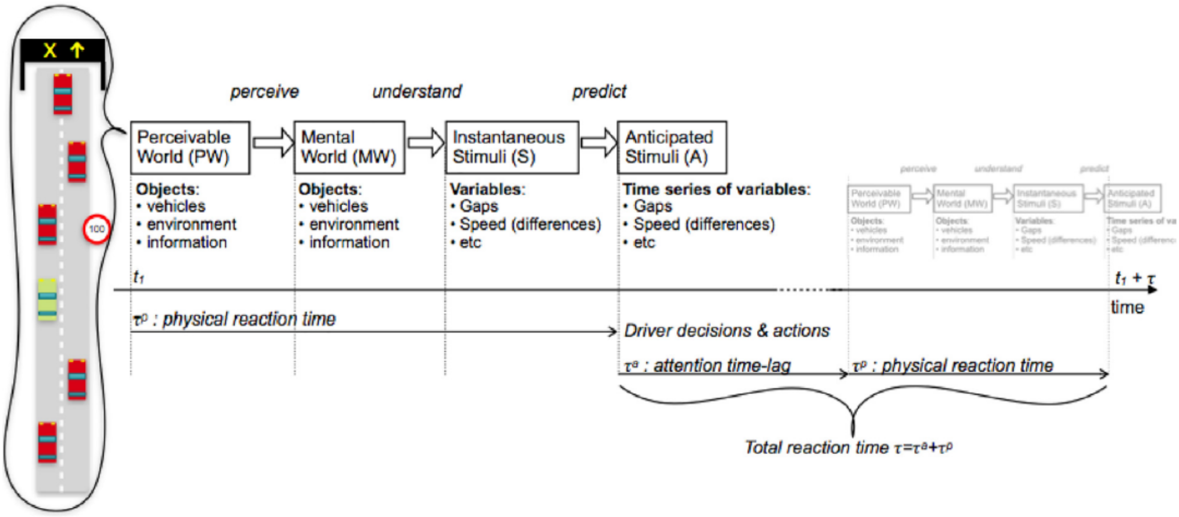


Figure 3.9: Situation Awareness concept as proposed in the context of driving by (Van Lint & Calvert, 2018)

The first mental model to elaborate is Endsley's Situation Awareness. Three levels are distinguished in figure 3.9. In the first level of the SA, the perception process exists, in which the perceivable environment is acknowledged through the sensory receptors of a human driver. This process is defined and governed not only by the biological capabilities of a human but also by their traits. The combination of the biological capabilities and the traits of a human driver, define and shape their mental state, and preferences. The second level regards the interpretation of the stimuli into meaningful information subject to goals. At the last level, the driver translates the events and the objects into near and immediate effects shortly in order to make the right decision. SA has many similarities with the models of (Wickens et al., 2015) and (Shinar, 1978) as all these mental models based on the information processing model, with an aim to define the way of the various mechanisms work. In the SA model, one can discern the time (reaction time) of the processing information needed until the execution of the response. The first component of the reaction time is called *physical reaction time*, which is the time to process the information from the level of perception to the level of response. It is evident that the physical reaction time is affected by the weather conditions as drivers need additional time to process the information. This conclusion outlined by numerous studies which the most representative among them,(Konstantopoulos, Chapman, & Crundall, 2010), revealed that drivers' eye had lower sampling rates and longer fixations in rain. The second component is the *attention time lag*, which is the result of the secondary information processing while driving. The summation of these two components makes up the total reaction time $\tau = \tau_i^a + \tau_i^p$. To this reaction time, processes for recalling the memory, either short term or long term memory is assumed to be included in the total reaction time. In our study, we will redefine the reaction time by following (Green, 2000) definitions as it is more applicable in our case study.

Among others, it is important to note at this point, the meaning of the memory into the concept of SA and HIP. As we explained before, (Wickens et al., 2015) distinguishes two types of memory that have a paramount role in the HIP model. The short-term memory (STM), also some researchers called it working memory, and the long-term memory (LTM) also called as permanent memory. In the following text, the differences and their function are outlined according to (Shinar, 1978):

- **Capacity**: The STM has a small capacity whereas the LTM has limitless capacity.

- **Mechanisms**: The STM may or may not transfer the perceived information to LTM.
- **Nature of information**: The information that is stored into the STM is in the vast majority visual or acoustic. This information pass on the LTM is typically semantic or conceptual.
- **Decay of Information**: The information stored in the STM can be there indefinitely but, as new information from the environment receive the last chunks of information are erased for the sake of new information. The information stored in the LTM is permanently there, but are not always retrievable.
- **Retrieval**: The information that remains in the STM are always retrievable. Nevertheless, the information in the LTM is not always retrievable due to inefficient search.

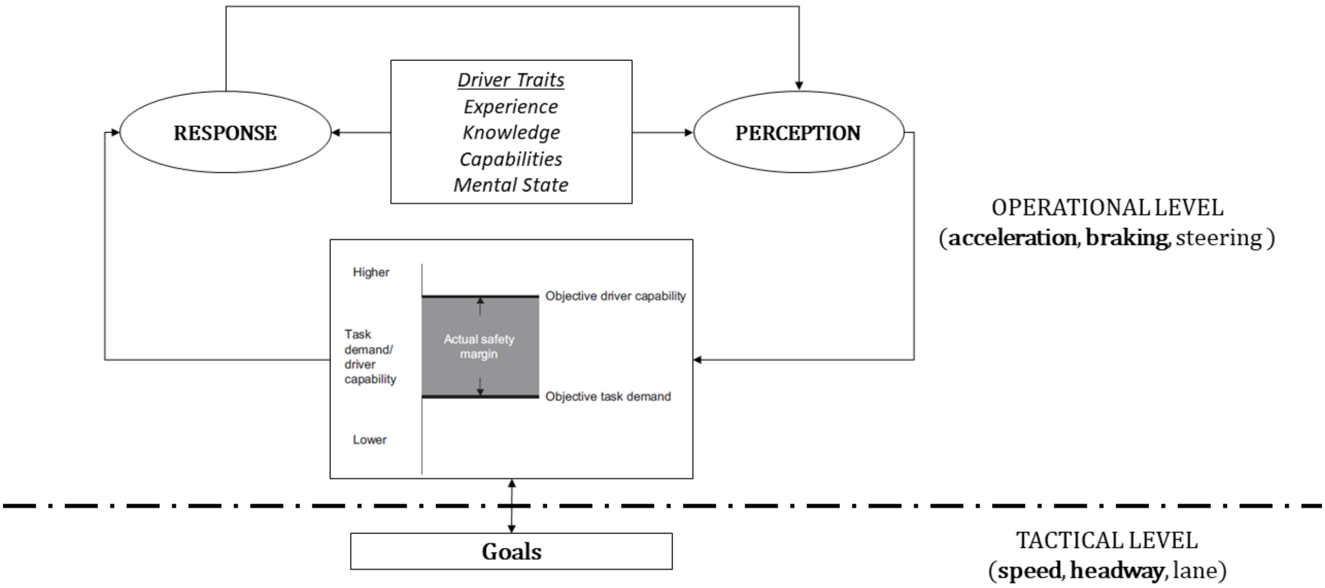


Figure 3.10: The two main human processes of perception and response, enriched with the Fullers model of TCI

As we have already mentioned above, a key concept to bear in mind is two HF processes; **perception** and **response**. SA covers the part of the perception. The next mental model is the TCI which covers the part of the response to the related subjective risk. Conceptually, an illustration of these two HF processes is provided in figure 3.10. In this figure, we can see the two main processes of perception and response, as well as the **behavioural adaptation** of the drivers which is a key principle in Fuller's Task capability interface (TCI). The drivers avoid collisions by monitoring the difference between task demand and task capability. Due to the variations between the driving's population traits and inaccuracies on the perception (and in response), divers act on their perceived task demand. That leads to the drivers to a perceived safety margin in which they act. It is rational to state that the smaller the safety margin the higher the risk of the drivers. The next section extends the multilevel framework by introducing plausible mechanisms that affect human behaviour in rainy conditions.

3.2.2 Conceptual Framework of Car Following in Rain

In this section, an extension of the original multilevel framework for microsimulation, as (Van Lint & Calvert, 2018) proposed, is outlined to account for the rain conditions. The present framework models the driving tasks in a multilayered way in which, at the highest level is a collision-free car-following model. In the present case,

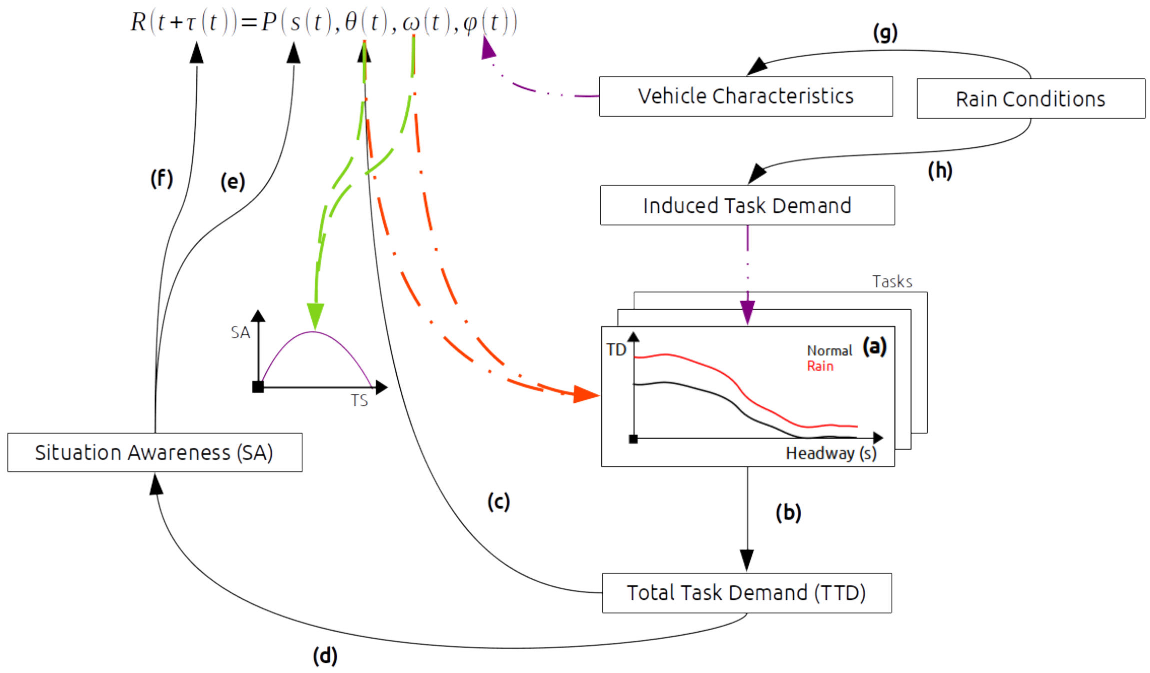


Figure 3.11: Conceptual Framework of the car following in rain conditions

the IDM+ was chosen for reasons that already explained in 3. Other car-following models are also applicable. At the lowest level, the cognitive behaviour of a driver is modelled. This is realized by introducing state variables such as the Task Demand, the Task Saturation and Situation Awareness that control; how many tasks a driver can handle and the level of human information processing from the environment. With the introduction of the weather conditions, the initial framework is extended by including representative elements of rainy conditions. Rain imposes a natural degradation to the performance of the vehicles due to the lower friction coefficient and also due to the imperfect control behaviour of the driver. Rain exerts perceptual difficulties in judging distances and speeds and at the same time reduces the sampling rate and fixation points of human eyes, leading them to suffer from higher physical reaction times.

The extended conceptual framework with the rain is illustrated in figure 3.12. The letters in the brackets are used as "way-points" to identify the functionality of the various parts in the framework and will be used further to elaborate on the mathematical formulation. The original framework of (Van Lint & Calvert, 2018) is recognizable in the framework with the letters (a)-(f), and the parts of the extended framework is indicated by the letters (g)-(h). The rain intensity predominantly affects the performance of the car itself as reduces the friction coefficient between the tires and the road surface.
The first effect is added to the original IDM+ model by the introduction of additional equations which embodies vehicle characteristics that hamper the performance of the vehicle. In the conceptual framework, this mechanism is denoted with the letters (g). The additional mathematical equation demand parameters that have to be chosen in advanced. We will try to demarcate ourselves by choosing the most necessary parameters in order to reduce the complexity of the model while inducing a lower computational burden to the simulation thereafter. The functions included in the model were presented earlier, in chapter 3.

The second impact on rain conditions is at a cognitive level. The studies of (R. G. Hoogendoorn, 2012), (Cacciabue & Carsten, 2010) have identified that rain conditions (generally weather conditions) affect the task demand of the car following task negatively. The more intense the precipitation, the more the induced task demand to drivers due to the hindered visibility. In the conceptual framework, the arrow namely (h) exerts an additional task difficulty to the task demand of the car following. The question which arises at this point is *how can we express the task difficulty of rain intensity with state variables of the traffic system which are observable and measurable?* An attempt to answer the question as simpler as possible while doing a strong assumption is given in the ensuing text. After the extensive literature review at a *macroscopic level* under rain conditions, we found that the traffic system has a negative correlation between rain intensity and capacity. A fundamental relationship between capacity and time headway is the following:

$$q_c = \frac{1}{h} \tag{3.18}$$

where q_c denotes the capacity of the road segment and h is the meantime headway as observed in the segment. A deep consideration here is the set of values of capacity reduction that we are about to be used in the current study. As mentioned above, a plethora of empirical studies yields different capacity reductions, which is logical as the capacity is a stochastic variable that depends on various other conditions. An elegant relationship that embodies the rain intensity and the capacity reduction had been proposed by the related work of (S. C. Calvert & Snelder, 2013) in which the capacity reduces approximately 1.9% per mm/h rain intensity. Let parameter f is the coefficient of reduction and ri is the rain intensity measured mm/h. The following equation gives the capacity of a roadway under rainy conditions:

$$q_c^R = (1 - f * ri) * q_c^N \tag{3.19}$$

This equation is data - derived. Without a doubt, depending on the data-set and the analysing process, one can derive various functional forms such as quadratic exponential etc. By following the reasoning of (Fuller, 2005) that postulates task demand can be explained at any time by the speed and the spacing of the vehicles, it is assumed that the **induced task demand** can be explained by the time headways[1] as well and defined by the following manner:

$$D^R = \frac{h^R}{h^N} * \gamma \tag{3.20}$$

where h^R is the observed time headway under rainy conditions, h^N is the observed time headway under normal conditions, D^R is the task difficulty due to rain and γ parameter is in this case equal to 1 as it is not clear evidence whether the relationship is linear or not. In this case and lack of any ground truth we assume that the relationship is linear. The same rationale of the relationship between time headways and task difficulty was followed by (Saifuzzaman et al., 2015) and (R. Hoogendoorn et al., 2013). The first authors combined the observed parameters of speed, distance headway and time headway into one equation that defines the so-called task difficulty. Further details of the mathematical formulation can be find elsewhere. The second authors translated the Fuller's postulation as as task difference between task demand and capability of the driver. This task difference was incorporated as a cubic function to the IDM model by a multiplicative parameter to the parameters of a_max, v_0, b_des, T. In addition to that, authors coined an another parabolic function which the dependent variable is the task demand. This last function is incorporated to the IDM model to the maximum acceleration to reflect the performance of the driver. Some empirical evidence of this correlation between cognitive loading and time headway recently is provided by (Pekkanen, Lappi, Itkonen, & Summala, 2017) suggesting that the time headway seems to be an index of task demand but not the only one. Substituting the equation 3.19 to the equation **??** with some algebraic manipulations we obtain the following expression:

$$D^R = \frac{1}{1 - f * ri} \tag{3.21}$$

By following this sensible way we achieve:

- To connect observed macroscopic data with microscopic variables.

1 The quotient of space headways and speeds give time headways $h = s_{i,j}/v_i$

- To derive a valid expression of induced task demand concerning the indications of the literature and the practice.
- To neglect the need for microscopic data for exhausting calibration.

Lastly, rain affects the reaction time of the drivers. One of the most frequently used HF trait that has been seen in the literature is the reaction time, defined τ_i. The reaction time as we already discussed is the composition of the physical reaction time and the lag time. Here, we will redefine the reaction time of the drivers in a more sensible way. Generally, reaction time is composed of the following components according to (Green, 2000):

- **Mental processing time (MPT)** is the time needed for a driver to perceive that a signal occurs and make a decision. MTP is further decomposed into:
  - *Sensation time (ST)* is the time it takes to detect an object on the road. Given that all the rest entities on a roadway remain the same, with better visibility conditions the reaction time decreases and vice versa.
  - *Perception Time (PT)* is the time needed to recognise the meaning of the stimuli.
  - *Response selection and programming* is the time needed to decide which response to make and mentally program the movement.
- **Movement time (MT)** is the time it takes for a driver to perform the movement with their muscles.
- **Device response time (DRT)** is the time it takes the physical device, the car, to perform its response.

That said, the perception reaction time for all the drivers defined as:

$$\tau = \tau_{MPT} + \cancelto{0}{\tau_{MT}} + \cancelto{0}{\tau_{DRT}} \tag{3.22}$$

where τ_{MPT} is the mental processing time, τ_{MT} is the movement reaction time, and τ_{DRT} is the device response time. For reasons of simplicity we will assume that the τ_{MT} and τ_{DRT} equal zero. In reality, these two processes demand from 100ms to a couple of 100ms (Treiber & Kesting, 2013b). The mental processing time τ_{MPT} is decomposed to sensation time τ_s, perception time τ_p, and response selection and programming τ_{rsp}. By looking at Figure 3.9 we will attempt to match each component of the mental processing time τ_{MPT} to the mental model of situation awareness. We can argue that the sensation time in the context of the situation awareness model matches with a part of level 1. The perception time matches with level 2 of situation awareness and the response selection and programming with level 3. What is discerned, the sensation time and the perception time will be affected the most under rainy conditions due to the difficulty to judge distances and relative speeds. It has been proven that the emergence of achromatic patches on a screen affect the reaction time of the drivers due to the difficulty of the humans to identify changes (Rensink, Kevin O'Regan, & Clark, 2000). In addition to that, (Yantis, 1993) had found that even if the luminance remain the same but new objects appear, human attracted by these new objects leading them to an increased reaction time. This finding was used in the study of (Konstantopoulos et al., 2010) as a theoretical explanation of the degraded visual search that leads to increased reaction times. Thus, we assume that the increase in cognitive load due to the decreased visibility will proportionally affect both sensation time and perception time.

$$\tau = (\tau_s + \tau_p) * (1 + \epsilon_i^{SA}(t)) + \cancelto{0}{\tau_{rsp}} \tag{3.23}$$

We can assume that the sensation time and the perception time under normal circumstances can reach up to 0.6 s. Under rainy conditions though, the additional task demand will exert a lag to the reaction time. The difference $SA_i^{max} - SA_i(t)$ is denoted as ϵ_{iSA}. The proposed model does not contain any anticipation mechanism, thus we can assume that the τ_{rsp} is equal to zero to account for anticipation mechanisms. By introducing time delay to the IDM+ we effectively transform an ordinary differential equation to a delay differential equation (Treiber & Kesting, 2013a). By increasing the reaction time to very high values, the system of "cars" will become unstable. Intuitively, the driving population will respond timid to the stimuli, leading the system to major oscillations due to overcompensating reactions. This behaviour will result in the generation of emergent traffic patterns that do not reflect real circumstances.

3.2.3 Fundamental Diagrams of Task Demand

In this study, we consider the task demand of car following. From the literature, we suspect that the rain imposes an induced task demand to the task of car-following. We will enrich the task demand by following the methodology in section 3.2. Since the only task in this research is the car following, we defined it as TD_i^{CF}. The following **assumptions** are made in order to construct the FDTD of the car following:

- The task demand is a function of the time headway (h).
- Drivers in dense traffic conditions experience high levels of task demand due to the denser environment and the subsequent more information loading to the memory. The opposite stands for light traffic conditions (or empty road(s)).
- It is also assumed that even if the drivers are on an empty road (i.e. $h \approx \infty$) experience low task demand.
- For small-time headways human drivers needs to utilize a large amount of their mental resources (Task Capacity). For very large time headways, larger than an arbitrary value of h_i^0, human drivers experience lower Task Demand. A valid threshold value can be $h_i^0 = 3s$ as (Lewis-Evans, De Waard, & Brookhuis, 2010) revealed in their exploratory study.
- According to the studies (R. G. Hoogendoorn, 2012) and (Fuller, 2011), task demand is assumed to be more difficult than the normal conditions. In order to incorporate this assumption in our model, an additional multiplicative parameter D is introduced to the original task demand function. With this manner, we can allow a driver to experience higher task demand imposed by the rain.

In the recent literature, we have seen various structural functions that represent the Task Demand. This implementation was realised by either choosing a piece-wise function (Van Lint & Calvert, 2018), (S. Calvert et al., 2020), or fuzzy logic functions (Cacciabue & Carsten, 2010) or continuous functions in the form of exponential decay (S. C. Calvert et al., 2020). The following continuous mathematical equation summarizes the afore-mentioned assumptions:

$$TD_i(h) = D^R * \begin{cases} TD_i^{max} & h \leq h_i^{min} \\ TD_i^{max} - \frac{h - h_i^{min}}{h_i^{min}(a) - h_i^0} * (TD_i^{max} - TDi^0) & h_i^{min} < h \leq h_i^0 \\ TD_i^0 & h > h_i^0 \end{cases} \tag{3.24}$$

where $TD_i^(h)$ is the task demand experienced by a driver i as a function of time headway h, h_{exp} is the level of exponential decay as the time headway increases. The exponential decay here seems rational option to use as the drivers even with large headways will still experienced task demand. Particularly, with the emergence of weather conditions, driver will experience higher levels of demands than driving under normal conditions. The multiplicative factor of additional task difficulty D^R is obtained by the methodology that was described above.

3.2.4 Situation Awareness

Situation Awareness(SA) relates the performance of a driver (workload) through Task Saturation(TS) by using the FDTD. The TS is defined as the total task(s) demand to a static(dynamic) capacity of each driver. The assumptions for the construction of the diagram of SA are the followings:

- For low levels of TS, a driver is fully aware of its environment.
- After a certain point, which we defined as TS_{crit}, the SA of a driver deteriorates.
- After a certain point of TS, which we named TS_{max} and $TS_{max} > TS_{crit}$, the SA levels reach the lowest mental state and no further degradation is observed.

The mathematical formulation is specified in the following piecewise expression:

$$SA_i(TS_i(t), t) = \begin{cases} SA_i^{max} & TS_i(t) < TS_i^{crit} \\ SA_i^{max} - \frac{TS_i(t) - TS_i^{crit}}{TS_i^{max} - TS_i^{crit}} * (SA_i^{max} - SA_i^{min}) & TS_i^{crit} \leq TS_i(t) < TS_i^{max} \\ SA_i^{min} & TS_i(t) \geq TS_i^{max} \end{cases} \tag{3.25}$$

In equation 3.25, $SA_i^{max} = 1.0$, $SA_i^{min} = 0.5$ reflect me maximum and minimum SA metal levels. $TS_i^{crit} = 0.8$ reflects the so-called the critical task saturation above which the SA starts deteriorating. $TS_i^{max} = 2.0$ is the maximum saturation level above which SA reaches the lowest levels with no further degradation.

3.2.5 Perception Errors

It has been proven that human drivers have systematic biases towards estimating speeds and distances. For example, under normal driving conditions, while driving for a prolonged time at high speeds (highway), and suddenly enter a zone with speed restrictions, most of the drivers underestimate their speeds and perceive that travelling faster (Martens, Comte, & Kaptein, 1997). Another example of the distance perception biases has given by (Nilsson, 2000) that suggests distance headways are generally underestimated, and especially the rear gaps. At the same conclusions and more insights was given by (Hiro, 1996). More specifically the last author suggests that:

- The relationship between objective distance and estimated distance is linear.
- The higher the speed of a vehicle, the smaller the slope of the linear function of the distance underestimation; That is the perception errors are larger.
- The most important factor for distance underestimation is the movement of the retinal image.

$$s_i^p = (1 + \delta_i * \epsilon_i^{SA}(t)) * s_i \tag{3.26}$$

$$\Delta v_i^p = (1 + \delta_i * \epsilon_i^{SA}(t)) * \Delta v_i \tag{3.27}$$

and

$$\delta_i = \begin{cases} 1 \\ -1 \end{cases} \tag{3.28}$$

For the present study, we experiment with probabilities. We assume that the vast majority of the drivers underestimate the stimuli. On the contrary, in the case of fog, as we will discuss, the exact opposite happens; most of the drivers seem to overestimate rather than underestimate the stimuli. Particularly, for speed estimation, the literature suggests a difficulty to conclude whether drivers overestimate or underestimate. For this reason, we assume that speed differences are subjected to the same biases as distances. In the end, we give a small probability that some drivers overestimate the stimuli. That said, the percentage of the drivers that underestimate gaps and speed differences is 75% while 25% those who overestimate the stimuli.

3.2.6 Behavioural Adaptation

Drivers need to adjust their behaviour, i.e. the variables that control when driving (desired speed and headway), in order to compensate for the negative effects imposed by inclement weather conditions. The principle of behavioural adaptation which have been seen in (Näätänen & Summala, 1974) and (Fuller, 2005) for instance as a mechanism to reduce risk, is of a pivotal point when discussing adverse weather conditions. In the ensuing text, we present a manner to mathematically incorporate the behavioural adaptation in a car following in an effort to generate the collective dynamics of traffic under rainy conditions.

One crucial point to substantiate here is the behavioural adaptation emerges at a tactical level. Therefore, a driver make decisions at a tactical level regarding their preference speed (desired speed v_0) and headway (desired headway T). In the case of rain, the behavioural adaptation that is observed is the reduction of the desired speed and increase of the desired headways as numerous of studies indicate (Ahmed & Ghasemzadeh, 2018), (Hammit et al., 2018), (Hamdar et al., 2008), (Hammit et al., 2019). The magnitude of the reduction (desired speed) and the increment (time headways) is calculated as a function of the TS. In simple terms, the behavioural adaptation is triggered by the motivation of the drivers to reduce the high amount of information which is related with the risk:

$$\epsilon_i^{TS}(t) = argmax(0, TS_i(t) - TS_i^{crit}(t)) \tag{3.29}$$

The first mechanism that governs the desired speed is formulated as follows:

$$v_i = (1 - \epsilon_i^{TS}(t)) * v_i^0 \tag{3.30}$$

The second mechanism that governs the desired headway is the following:

$$T_i = (1 + \epsilon_i^{TS}(t)) * T_i^0 \tag{3.31}$$

This mathematical formulation describes homeostasis theory of (Fuller, 2011). Driver seeks to relief their high workload by following strategies that permit them to do so. The combination of these two strategies described above is actually observed in real traffic operations. The magnitude of the adaptation at each strategy in this thesis is obtained by the equation 3.2.6. The difference between critical task saturation and task saturation is translated as a perceived risk. It is evident from the formulation of $\epsilon_i^{TS}(t)$ that the higher the risk, the larger the response adaptation in the equations 5.3, 3.31. We can also argue that the second mechanism of regulating the desired headway is stemming from the fact that the drivers aim at increasing their distance with their predecessor to avoid occlusions on their visual field due to the generated spray from the leading vehicle. A phenomenon that is usually can be found at the highways when vehicles travelling with a high speed. The following assumptions made for the mathematical formulation of the behavioural adaptation decision-making mechanism:

- Predominantly, drivers seek while motivated to maintain a certain risk level so at to drive safely.
- The parameters that regulate the perceived risk are the desired speed and desired headway.
- The difference between nominal Critical Task Saturation and subjective Task Saturation defines the magnitude of the adaptation mechanisms.
- The magnitude of adaptation is analogous to the difference between subjective Task Saturation and Critical Task Saturation.

3.2.7 Heterogeneity

Heterogeneity in car following indicates the different driving styles between the driving population. It has been shown that the impact of heterogeneity in a car following behaviour is substantial, (Ossen & Hoogendoorn, 2007). In essence, the inter-driver heterogeneity, cannot be that simple model in simulations frameworks as simple observed empirically. That had been proved by the work of (Ossen & Hoogendoorn, 2007) wherein there is no mechanism indicating that with some fixed values of acceleration and reaction time the traffic will become unstable. Nonetheless, the heterogeneity is deemed by some authors (Ossen & Hoogendoorn, 2011) as a substance to microscopic modelling as it can yields better traffic representation and improved predictive performance. In the present framework, the heterogeneity can be connected with the task capacity of the drivers. Thus, the heterogeneity of the drivers is expressed in terms of varying Task capacity. The following formula can be embedded in the simulations:

$$TC_i = min(TC_{max}, max(TC_{min}, 1 + \psi_i) \tag{3.32}$$

where TC_i is the task capacity of the driver i, $TC_{max} = 1.1$ is the maximum Task Capacity $TC_{min} = 0.9$, and ψ_i is a parameter that follows a normal distribution with zero mean and 0.1 standard deviation, N[0.0.1]. The maximum Task Capacity we assume takes an arbitrary value of 1.1. The minimum Task capacity is set equal to 0.9. The TC of a vehicle i affects Task Saturation. This in turns affects the shape of the fundamental diagram of task demand and the extend of adaptation strategies. Another effect that we assume to have is on the perception errors. The larger the value of TC the lower the perceptual biases and vice versa.

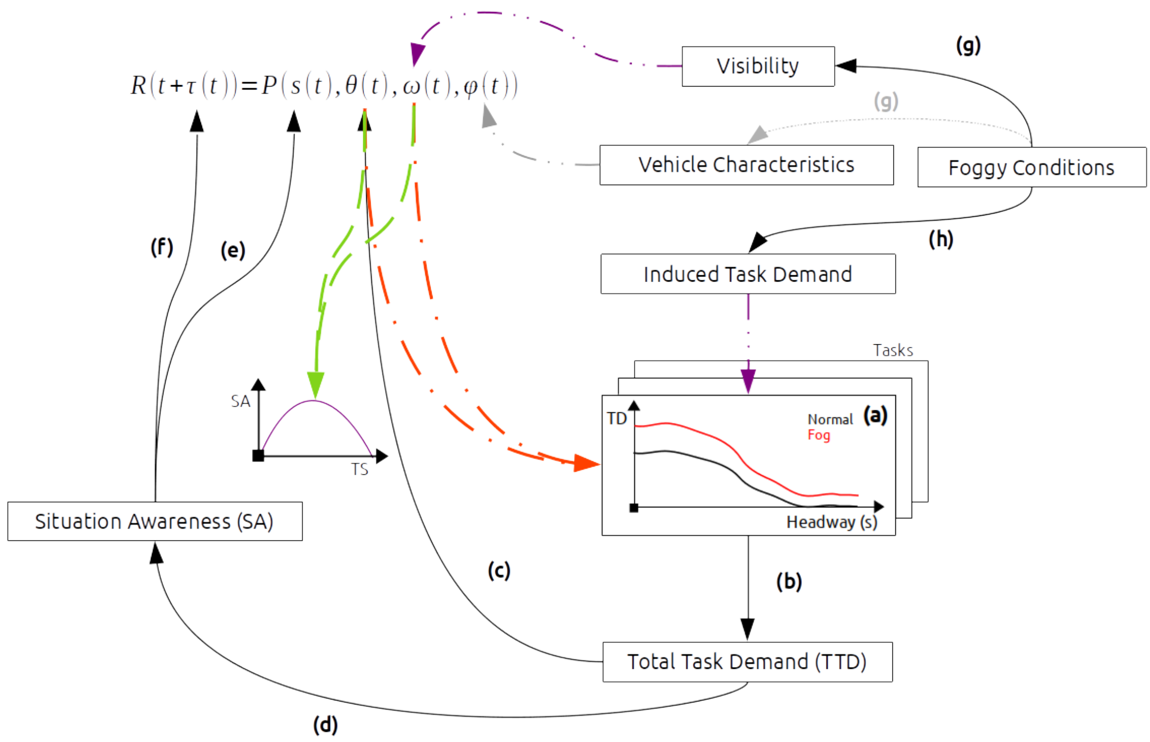


Figure 3.12: Conceptual Framework of the car following in foggy conditions

3.2.8 Conceptual Framework of car following in Fog

This section aims at extending the generic multi-level framework as presented in Figure 3.8 by introducing mechanisms that explain the driving behaviour under foggy conditions. At the higher level, the vehicle kinematics are governed by the IDM+ model with some modifications as presented in the previous chapter. At the lower level, mechanisms that govern the cognitive behaviour and goals are in place. To understand the peculiarity of fog on human drivers perception and their subsequent response the following example is given. Studies had been shown[2] that most of the drivers, when the visibility is lower than 200m, are willing to reduce their space headways to their preceding vehicle (White & Jeffery, 1980). At a visibility of 150m, a staggering proportion of 30% of the drivers maintained a time headway within 2s. These results indicate a unique aggregate behaviour of the divers that are attributed to; the interactions in the traffic and physio-cognitive mechanisms. Normally, one can expect that drivers want to increased space headway in order to compensate/avoid high risk circumstances.

The first studies conducted on a driving simulator such as (Snowden, Stimpson, & Ruddle, 1998), (Owens, Wood, & Carberry, 2010) showed that the drivers systematically tend to underestimate the speeds. Studies like the previous have found to have an important deficit. The fog in the simulator was emulated in a distant-independent way. In other words, the reduction of the contrast was uniformly distributed. That makes the results of the model unreliable to draw any conclusions regarding the perception biases of the drivers and the accompanying adaptation effects. The most recent developments suggest that a technique to emulate foggy conditions is the distance-dependent contrast reduction. By using this technique, the object further away of the driver cannot be discern. The studies that adopted this technique,(Pretto, Bresciani, Rainer, & Bülthoff, 2012), (Saffarian, Happee, & de Winter, 2012), (Cavallo, 2002), (Caro, Cavallo, Marendaz, Boer, & Vienne, 2007) resulted at the same conclusion; the speed is overestimated.

As it is evident from the previous studies, the real problems of safety arise when the threshold of visible objects

2 Empirical and simulator studies

is below 50m when the drivers are not able to come to standstill position timely (Sumner, Baguley, & Burton, 1977). From 1980 and even earlier than that, a well established equation that connects perceived distances with actual distances is in a power-law form (Hills, 1980). In the experiment of (Cavallo, 2002) a condition of high density fog was emulated with the technique of exponential decay in order to understand weather the perceptual mechanism of judging the distance headways is altered. A relationship between the estimated and actual distance was formulated and it can be described with the following power function:

$$\Delta s_{i,j}^{e} = 0.48 * \Delta s_{i,j}^{0.48} \tag{3.33}$$

The equation 3.33 is a physiological mechanism that describes the systematic errors when perceiving distances. one can obtain a better picture of the mechanism by looking at Figure 3.13.

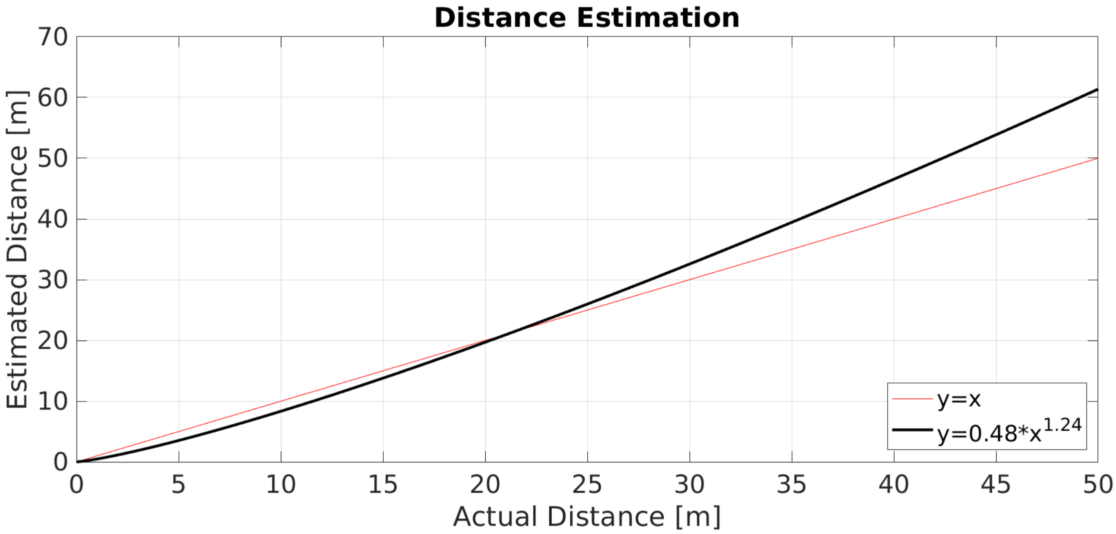


Figure 3.13: Distance Estimation attributed only to physiological mechanism of eyes

At the distance of 21 meters, drivers start to overestimate the space headways in a exponential trend. This overestimation of distance headways probably leads the drivers to drive closely to their leading vehicle in foggy conditions. The question which arises is *what is the impact of cognitive load on the perception stimuli?* As the present framework has been constructed, it is assumed that the reduced situation awareness of a drivers lead a human driver to make "mistakes" on the judgement of the stimuli. We can further assume, with respect to the study of (Van Lint & Calvert, 2018) that the previous assumptions still holds and the reduced situation awareness can exacerbate the already misconceived distance. The following equation describes the assumptions:

$$\Delta s_{i,j}^{e,c} = \epsilon_i^{SA}(t) * \Delta s_{i,j}^{e} \tag{3.34}$$

where $\epsilon_i^{SA}(t) = SA_i^{max} - SA_i(t)$
As a general conclusion derived from (R. G. Hoogendoorn et al., 2011) is that the vast majority of the driving population decrease their speed while increasing their headway. However, some of the drivers drove even faster than normal conditions. This allegation relies upon the fact that the drivers losing the capacity of the visual cues regarding speed. To the same conclusion have been reached by (Pretto et al., 2012). Drivers **overestimate** the speed leading them to decelerate. That said, we can suggest that the perception biases of drivers due to fog (hindered awareness) point towards overestimation. The objective speed differences and headway are obtained by $\Delta v_{i,j}$ and $s_{i,j}$. The estimated errors due to reduced perception abilities is given by:

$$\Delta v_{i,j}^{e} = \xi(t) * \Delta v_{i,j} \tag{3.35}$$

The factor $\xi(t)$ is a function that embodies the mental state of each driver ($SA_i(t)$) and a factor γ which is describes towards what direction the drivers estimating their stimuli (over- underestimation). The formulation is the one below:

$$\xi_{i(t)} = (1 + \gamma * (SA_i^{max} - SA_i(t))) \tag{3.36}$$

The γ parameter is binary, taking values either 1 or -1, depending what phenomenon is studied and the indications given by the literature. In case we have an indication about the reaction time impairment, we can incorporate it as well.

3.2.9 Behavioral Adaptation in fog

As we discussed in the previous section, the driver's behavioural adaptation emerges in both weather phenomena as a compensation mechanism to reduce their perceived risk. The literature and empirical observations thought, pointing towards the desired speed adaptation mechanism as the one and only strategy of risk reduction. There is a large body of literature which reveal this adaptation mechanism. Some vivid examples are given to understand better the phenomenon. In the study of (Sumner et al., 1977) on the highway M4 clearly shows that the drivers, when they are not instructed by the warning system to maintain a certain speed, they choose to reduce their desired speed. Supplementary to this, the study of (Edwards, 1999) results at the same conclusions.

When looking at some simulator studies, a remarkable phenomenon has been observed during foggy conditions. Drivers aiming to stay within visual contact with the leading vehicle. Theoretical explanations of this phenomenon postulate that drivers feel safer to see what the following. To expand further, it has been shown that the drivers can perceive better the stimuli of headways and speed differences when closely driving. Nevertheless, these allegations are giving breeding ground to the research, but in real traffic operations, it has not been observed such phenomenon. This headway reduction (or keeping), probably is not a derivative of intentional behaviour of the drivers, on the contrary, it could be a derivative of the interactions of the drivers while suffering from reduced perceptual abilities.(references)

It is rational then to not impose any mechanism to the preferred time headways , in the way we did in the rain conditions. Instead, we impose a compensation mechanism that governs the desired speed and is formulated with the following manner:

$$v_i^0 = (1 - \beta_i^{v_0} \epsilon_i^{TS}(t)) * v_i^0 \tag{3.37}$$

where v_i^0 is the desired speed, $\epsilon_i^{TS}(t)$ is the task saturation of a given vehicle i, and $\beta_i^{v_0}$ is a parameter which reflects the maximum reduction of the desired speed. The last parameter is set to the value of 90%.

3.3 SUB - CONCLUSIONS

In this chapter, the theoretical framework was illustrated. In this framework we can distinguish two components; (1) The model that governs the longitudinal movement of the vehicle and (2) the model that govern the mental state of the drivers.

The longitudinal model is the IDM+ to its core with the inclusion of additional mathematical formulation for the parameters of maximum acceleration and maximum deceleration. The formulation for the maximum acceleration is a function of the engines' force and the rolling resistance. Accordingly, the formulation of maximum deceleration is a function of rain intensity which also includes the parameter of friction coefficient. To test the effectiveness of the model, a simple car following experiment is set to MatLab. A Latin Hypercube Sampling used to assess the sensitivity of the two main parameters of the model which will be used later, the friction coefficient and the rain intensity. The preliminary results showed that the proposed formulation is effective to account for rainy conditions. Nevertheless, assumptions made on the additional parameters which we include. These assumptions are based on previous studies, the literature and empirical evidence.

The mental model of the framework is extended in order to account for the additional task demand of fog or rain. In the absence of any mathematical formulation that governs the fog and the mental capabilities we follow the ensuing method. The rationale is rather simple and generic, but it is accompanied with some assumption which we are going to discuss further. The empirical evidence suggest that the fog, for instance, has a negative impact on the aggregate traffic in terms of capacity. The more the fog intensity, the more the capacity degradation. The fundamental relationship between macroscopic and microscopic is given by the relationship $q_c = 1/h$. Therefore, with that manner, the observed aggregate results are translated into desegregated as way of increased task demand.

The model that governs the mental state of the drivers is based on the theoretical framework as coined by (Van Lint & Calvert, 2018). In this framework, two main mental models are accounted for, Endsley's Situation awareness and Fuller's TCI. The first model explains how a human driver processes visual information. In its simplest form, three mechanisms constitute the model, the perception, the interpretation and the prediction (anticipation). There are also some "hidden" mechanisms in the mental construct of situation awareness; the first is the allocation of resources and the second is the role of the memory. The desicion making mechanism instead, is Incorporated by the use of TCI. The second mental model explains how the drivers decide the variables of desired speed and headway. It is assumed that the underlying mechanism that motivates a driver to adapt its behaviour is the excess of task demand. When the task demand surpasses the driver's capability, drivers motivated to follow adaptation strategies to reduce this task overloading. The framework that it is adopted in this study has many assumptions, which some of them worth mentioning further.

The drivers suffer from perception errors when driving under foggy or rainy conditions. Besides, the reaction time of the drivers is increased due to additional information processing time. These two assumptions form a good line for our hypothesis and the subsequent scenarios.

Another of significance point mechanism is the anticipation of the drivers. According to (Treiber & Kesting, 2013a), anticipation, temporal or spatial, is an important compensation mechanism for alleviating the timid reaction due to overestimation or underestimation capabilities. The mechanism of temporal anticipation will be tested in the scenarios to see the performance of the traffic flow. The formal hypothesis will be formed in the next chapter.

Yet, although the significant empirical evidence that indicate adaptations in driving **whether the drivers follow a specific adaptation strategy, especially in the case of rain and fog**. The previous statement forms a very good basis for hypothesizing that the drivers either adapt their speed or headways or both during weather events. In the case of fog, the literature suggests that some of the drivers follow a speed adaptation strategy, while some others continue driving close to the leading vehicles. In the case of rain, the drivers adapt both speed and headways. The previous allegation based on the degraded performance of the network. These hypotheses will be elaborated in detail in the following chapter.

At this point, the following sub-questions are answered:

- What mental constructs are to be exploited in the study?
  Two are the main mental constructs that are utilised in this study; the first is the Fuller's Task Capacity Interface (TCI) and the second is Endsley's Situation Awareness. TCI in simple terms is a comparator between the subjective driver's capability and task demand subject to the driver's biological and constitutional characteristics. It predominately concerns the behaviour of the drivers at the operational level but is also being affected from the tactical level as the goals of speed and headway stemming from this level. SA is a concept that is usually can be found elsewhere especially in aviation research. This concept is powerful as it combines three basic elements (levels) that reflects human behaviour. These levels are Perception, Comprehension and Projection in a future state. Within this powerful construct, we can model dynamic systems and trace the mental trajectories for potential irregularities while the explanatory power is its main trait.

- What parameters define the cognitive mental state of a human driver?
  The state-space parameters that define the mental state of a driver are mainly two, the SA and the TD. These two parameters address the mental state of a given driver at any time instant and are inversely related with each other. When SA is high, the TD is low and vice versa. SA in this specific framework captures level 2 of Endsley's SA that is Comprehension. We explicitly assume that comprehension is related to the quality of the stimuli and the prolonged reaction times. Furthermore, we assume that these

two mental constructs are related through a proxy parameter of TS (Task Saturation). This parameter is the quotient of task demand and capacity. Therefore, SA is a function of TS, at a given time instant t. TD is a function of time headway, and this assumption holds good as in the literature of human factors indicated such a relationship. Further than that, the only one task that we consider here, car-following, is rather a generalisation as a car following task can enclose various sub-tasks. However, for the sake of this study, and the luck of any other empirical evidence, we consider that this task can serve its purpose.

- How these human factors can be modelled mathematically in a simulation experiment?
  The biggest challenge of this framework is the lack of empirical evidence of any mathematical relationship between the mental constructs that are utilized. Generally speaking, these mental constructs for most of the cases are latent variables, i.e. they are observed through biological indicators in a form of regression models or structural equations. The influence of the mental parameters is not known, yet, but they are assumed and hypothesised. That said, the so-called FDTD is formulated as a piece-wise relationship with the linear and proportional influence of the involved parameters. The SA mathematical formulation is again a piece-wise relationship with the proportional influence of the involved parameters.

- How the weather conditions of rain and fog can be reasonably incorporated into such a framework?
  Research indicated various ways to incorporate the weather conditions of fog and rain into mathematical models. For the case of rain, we can discern two different approaches to incorporate the rainy conditions which work as one. The one way is from the mechanical side of the mathematical formulation that encloses additional parameters which can address the agility of a vehicle on a wet road. Maybe, the most important parameter of this proposed formulation is the friction coefficient which is constantly neglected from the microscopic traffic flow models. As we mentioned above, there are additional parameters of the vehicle mass per se, the tractive effort of the engine and the rolling coefficient of the wheels to name a few. These parameters are obtained from the literature and the values as well. The second way that we have to consider is the cognitive state differentiation of the human driver. Due to the reduced visibility of raindrops of the windscreen, and the combination of the operation of the wipers, drivers tend to slow down and leaving larger time headways from their predecessor. Exactly where is the core of our next assumption? We assume that a representative **performance measure** of the traffic stream is the time headways. From this fact, in combination with the FDTD as proposed, and with some algebraic manipulations, we derive that the more rainy conditions, the more **induced task demand** a driver will suffer.
  For the fog case, we consider that the driver's cognition will only suffer due to the reduced visibility and the subsequently degraded perception. For the relationship of distance estimation, we know a closed-form power-law function that connects the bias of the distance depending on the actual distance. This bias relates only to the deficiency of the visual acuity of the drivers. We further assume that the mental state of the drivers will exert an additional impact on the already biased distance towards the direction that is governed from the power-law form equation. For speed perception, there is a shred of ample evidence in the literature towards overestimation. To attain such results we utilize the concept of the induced task difficulty again yielded from the empirical evidence.

Now, we can adequately answer to the second research subquestion:

- What is the most appropriate modeling framework to be exploited in this study?
  The most appropriate modelling framework that we use in the present study is the one that proposed by (Van Lint & Calvert, 2018). This framework due to its multilevel conceptualization combines different mental constructs with a collision-free car following model makes it easily extendable and adaptable depending on the phenomenon which is studied.

4 SIMULATION STUDY: A CASE OF AN INDUCED PERTURBATION IN TRAFFIC STREAM

Traffic simulation is one of the most frequently used experimental techniques for the transport planners and engineers. Over the years, many simulation packages have been developed with different capabilities, scope (microscopic, mesoscopic macroscopic, hybrid), behaviour models (longitudinal and latitudinal) and simulation logic. In this study, MatLab is adopted as a "physical laboratory" to experiment the hypotheses we form. The code that has been developed for the purpose of this thesis can be found in https://github.com/DimitrisKokoris/Thesis.git The remainder of this chapter is organized as follows; In section 4.1 we discuss the design of the experiments. We illustrate the set up of the road segment, the demand pattern, the hypotheses that lead us to the simulation scenarios and the KPI's to measure the network performance. After the set up of the experiment, we propose a base case scenario that works as a reference to compare the rest scenarios against it. In the same section we calibrate the proposed formulation to assess whether the chosen values of the parameters are sensible while can produce the same phenomena with the IDM+ without any cognitive mechanisms.

4.1 DESIGN OF EXPERIMENTS : MICROSCOPIC SIMULATION

Our goal is to assess the effectiveness of thr proposed framework, and thus a generic experiment is proposed. This experiment is a single lane road with an induced flow conserving bottlneck. With such an experiement we safeguard two aspects, the simplicity of the apparatus and the interactions between the agents (vehicles). In the ensuing sections all the technical aspects of the experiment are elaborated.

4.1.1 Road Stretch

In order to simulate the car following behaviour under adverse weather conditions while considering mechanism that explicitly govern the human behaviour (cognition and behavioural adaptation), the use of a single - lane road stretch is considered. The length of the road stretch is 6.000 [m] with a speed limit of [120 km/h] (33.33 [m/s]). The vehicles traversing the road stretch are identical with length of l = 5 [m] governed by the equations proposed in chapter 3. In order to check the consistency of the generated results with the underlying theory, we plot the fundamental diagrams of flow - density and the speed-density. For these calculations, we use the following equations:

$$\rho(x,t) = \frac{1}{x_{a-1}(t) - x_a(t)}, \forall a \in A \tag{4.1}$$

$$q(x,t) = \frac{1}{T_{a-1}(t) - T_a(t)}, \forall a \in A \tag{4.2}$$

where A is the set of all drivers, $a-1$ is the predecessor vehicle, a is the successor vehicle, the posistion x has units of meter and the time instant T has units of seconds, given that $x_{a-1} > x_a$ and $T_{a-1} > T_a$. For the base case when we use the equation of IDM+ model we have the following fundamental diagrams.
In table 4.1 are shown the infrastructure geometric characteristics and the additional operational entities.
The time horizon that we simulate each scenario is set to be 15 minutes (900 seconds). We neither consider a warming up period nor excluding road stretches. This is done because the stochastic processes are limited. The traffic demand and the capacity of the bottleneck are shown to figure 4.2. The demand on the highway starts at t=0 with 900 veh/h and at t=100s the throughput is set at 2200 veh/h. The throughput remains the same for a period of 250s. After this time, at t=350s, the demand is reduced at 900 veh/h till the end of the simulation, at

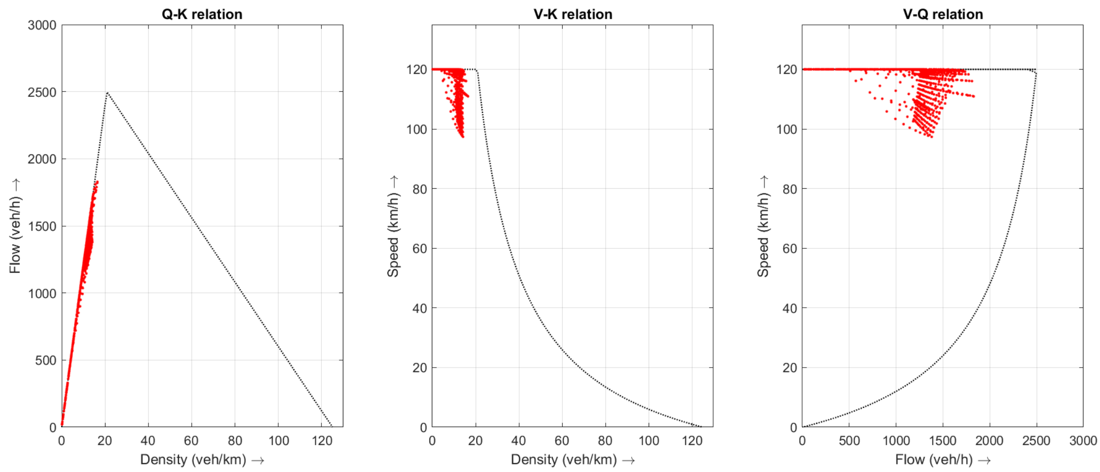


Figure 4.1: Demand pattern and capacity at the bottleneck

Table 4.1: Infrastructure Characteristics

Entity	Description / Value
Lanes	1
Direction	One-directional
Length	6000 [m]
Speed Limit	120 [km/h]

t=900s. The capacity of the bottleneck is set for the whole period at q=2000 veh/h. The methodology we choose to simulate a bottleneck is elaborated in the ensuing text.

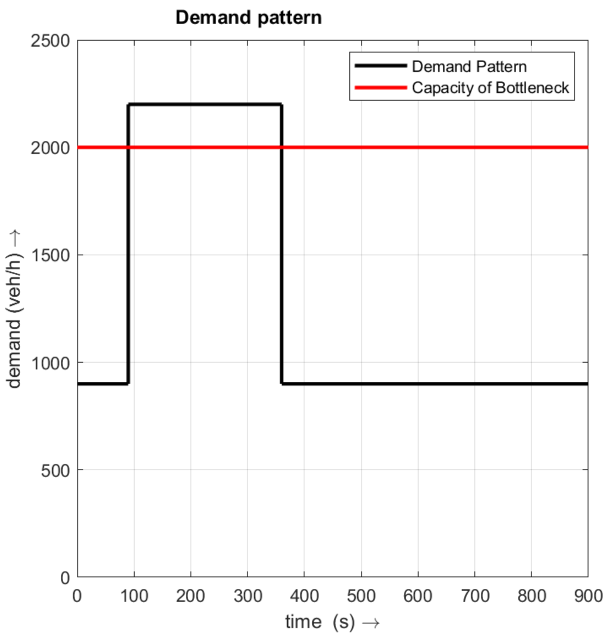


Figure 4.2: Demand pattern and capacity at the bottleneck

Normally, when simulating a one-way highway we cannot have any disturbance of a bottleneck. Nevertheless, we can set an artificial small perturbation to the traffic stream in order to create such an disruptive event. Flow conserving bottlenecks is easy to be implemented by spatially change parameters that govern the model equations. The most relevant candidates of this are the desired speed and the time headway. In addition, the change of these parameters have a meaningful interpretation as, the desired speed pertains to regions where speed limit is imposed, or sags (especially uphill segments), and time headway pertains to a safer driving due to narrow road segments, dangerous segments etc. The objective of setting this small-magnitude bottleneck is manifold. The first reason, is to disrupt traffic so as to assess whether the proposed framework is capable of reproducing plausible traffic patterns. The second reason is to evaluate if such a small disturbance can set traffic safety in danger with the combination of inclement weather and the hampered driver's mental state. Lastly, to be discussed further considerations about real traffic bottlenecks and what proactive measures can be taken in such weather events.

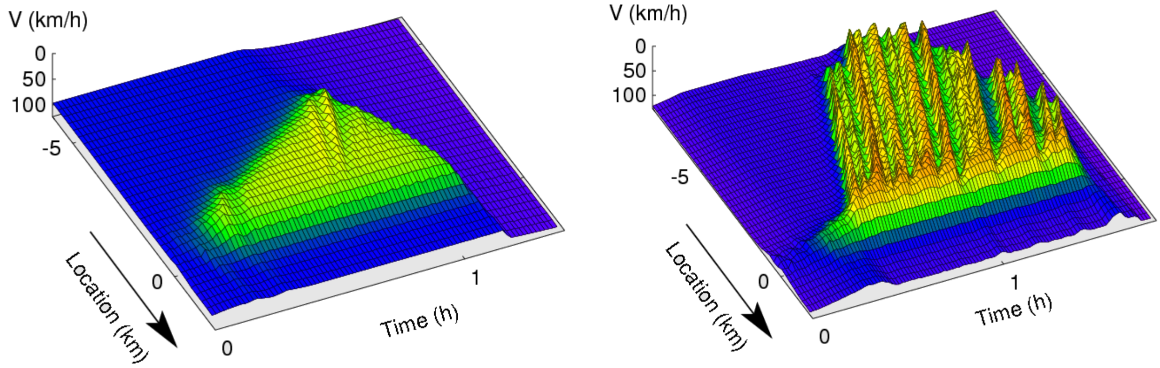
Naturally, the next question regards the magnitude of perturbation and the methodology of simulating it. It is assumed that a capacity drop of 250 [veh/h] is sufficient to simulate a small perturbations that will allow the traffic to interact. One can think of a traffic stream traversing a bridge or a narrow road segment. We follow the methodology of simulating it similarly to the work of (Treiber & Helbing, 2003) by locally increasing the time headway T. By exploiting this methodology, the flow is conserved when traversing of this road segment. The following steps summarize the methodology to activate the small perturbation:

- We set an artificial bottleneck with equilibrium capacity $q^{eq} = 2000$ veh/h.
- The maximum allowed speed of the road stretch is $v^{eq} = 120$ km/h.
- Using the fundamental equation $q^{eq} = \rho^{eq} * v^{eq}$, we calculate the density in the bottleneck as $\rho^{eq} = 16.67$ veh/km.
- The desired space headway of the vehicles driving at equilibrium conditions inside the bottleneck is given by:
  $s^*(v, \Delta v) = s_0 + v_n T + \cancelto{0}{\frac{v_n \Delta v_n}{2\sqrt{\alpha b}}}$
  Since the speed difference between two successive cars at equilibrium conditions is zero, the third member of the desired space equation is zero as well.
- Finally the fundamental equation between macroscopic and microscopic level connecting density and space headway is given by $\rho = 1000/(s_0 + l + v^{eq} * T)$, and hence the desired time headway equals to $T^b = 1.56s$.

The following piecewize equation covers all the cases of the desired time headway:

$$T_i = \begin{cases} T_i^0 & Base \\ T_i^b & 4km \leq x \leq 4.25km \\ T_i^0 * (1 + \epsilon(t)^{TS}) & Behavioral\,Adaptation \end{cases} \tag{4.3}$$

We impose this restriction to desired time headways starting at $x = 4000m$ for the next 250m to create the location of the bottleneck. Under normal traffic conditions by using the IDM+ model with the proposed modifications to the vehicle kinematics, we expect to obtain an aggregate traffic pattern as shown in figure 4.3(a). This type of pattern was generated by using IDM model and can be found at (Kesting, 2021). What we observe at this pattern is that the bottleneck created a disturbance to the traffic stream resulting to reduction in speed, and the creation of subtle oscillations.
On the contrary to the first traffic pattern as seen in Figure 4.3 (a), is the traffic pattern we observe at Figure 4.3 (b). This traffic pattern is obtained when of a higher severity bottleneck obstructs the free flow of the traffic stream. We expect that the combination of the mechanisms that we proposed to account for the weather conditions, will result into an aggregate traffic pattern as seen in Figure 4.3 (b). Nevertheless, the behavioral adaptation of the drivers on the parameters of desired speed and headways will lead the vehicles to have larger gaps in between and hence the perturbation may be vanished.



(a) Homogeneous Synchronised Traffic (HST) **(b)** Oscillating Congested Traffic (OCT)

Figure 4.3: Traffic patterns that produced with IDM model, (Kesting, 2021)

4.1.2 Hypotheses

In the theoretical framework, we assume that the adverse weather conditions influence the longitudinal driving behaviour by enabling cognitive mechanisms to the human driver and these result in a change to the driving behaviour. As a reminder we highlight that the fundamental mental constructs that applied in the theoretical framework are the TCI and the SA. Before setting all the proposed mechanisms to work simultaneously, we partition the conceptual framework into smaller parts, while though hypotheses, we assess the impacts of these different parts individually and collectively. Our aim here is to show that the propose conceptual framework, by making valid assumptions and simplifications, can explain the driving behaviour and emulate the traffic stream by generating performance competent to real life observations and behaviours.

Firstly, we introduce the mechanisms when driving under rainy conditions and form hypotheses for each part respectively. The first mechanism we apply is the one that physically degrades the performance of the vehicles. By performance we mean the agility of a vehicle in terms of acceleration or deceleration. It is known that the less the agility of the vehicles the more instabilities we can observe individually and collectively. In chapter 3 and especially in section 3.1 we have showed that the most influential factor on the equation of longitudinal motion is the friction coefficient. Friction coefficient affects the maximum acceleration and the maximum desired distance as it has a direct relationship with the conditions of the road surface. Therefore, the following hypothesis is proposed to allow the wet road surface to be introduced in the model:

- H_{0R}^{MVD} : Rain through friction coefficient does not alter the performance of the vehicle kinematics.
- H_{1R}^{MVD} : Alternative hypothesis it true.

This hypothesis is named as Mechanism of Vehicle Performance Degradation and abbreviated as MVD. Generally, the hypotheses we suggest are denoted with H while the superscripts are referring to the corresponding mechanisms and the subscripts denoted with 0 and 1 are the null and the alternative hypothesis respectively.

Secondly, we introduce mechanisms that affect the human's driver cognition. To explicitly account such mechanism, we make use the fundamental diagram of task demand as described section 3.2.3. In addition to that, we hypothesize that the adverse weather conditions influence the task of car following per se by introducing the influencing parameter D^R. A detailed explanation of how to estimate this influencing parameter was given in chapter 3. To operationalize the FDTD we assume that the various tasks (in this research the only task we have is the car following) has an additive effect on human cognition. In strict mathematical terms, this translated as an additive operation. By that, we calculate the TTD and the TS which in turn, we end up yo an overloading human mental workload. This degradation has an negative effect on *situation awareness* (level 2 understanding) and subsequently increased *reaction times* and/or *biased perception errors*. In addition to this, we hypothesize that:

- H_{0R}^{ITD} : Weather conditions, does not influence the task of car following.

- H_{1R}^{ITD} : Alternative hypothesis is true.

That said, the next sensible hypothesis we make while allowing the mechanism to work next to the MVD is:

- H_{0R}^{RT} : Reaction time does not affect the performance of the traffic stream.
- H_{1R}^{RT} : Alternative hypothesis accepted.

This mechanism is named as Mechanism of Reaction Time and the diminutive name is referred as MRT. This hypothesis fundamentally does not hold as it is well known that the larger the reaction times o vehicles, the more unstable becomes the traffic stream. As we mentioned before, we assume that the deteriorated SA (level 2) has a proportional influence on the deterioration of the reaction times, and that is the mechanism describes. Thereafter, we allow one more mechanism to work, the mechanism of Mechanism of Perception Errors (MPE). The hypothesis that we suggest is:

- H_{0R}^{PQ} : Rain does not exert perceptual biases to the drivers.
- H_{1R}^{PQ} : Alternative hypothesis stands.

Here we will enable the MPE and will allow the degraded SA (level 2) will proportionally influence the stimuli of relative gaps and relative speeds. The direction in which the biases have a propensity can be seen in chapter Nest step is to allow behavioural adaptation mechanisms in the framework in order to investigate the impacts on the traffic stream when the theory of risk allostasis is accounted. That is, the drivers dynamically regulate the perceived risk by comparing their capabilities and task demands and subsequently regulating their perceived risk by adapting the control parameters of time headway and desired speed at a tactical level. We apprise the reader to follow the closed loop in Figure 3.10 for further clarification. Naturally, the preceding assumptions are embodied into the following hypothesis:

- H_{0R}^{AD} : Drivers do not follow any adaptation strategy at a tactical level under the exposure of rain.
- H_{1R}^{AD} : Alternative hypothesis stands.

Lastly, we enable the inter-driving differences are captured by modelling the concept of heterogeneity. As we previously discussed, heterogeneity is considered, by any authors, as a substance to the microscopic simulations as it can generate the traffic stream behaviour more realistic. We can think of many things to modulate to achieve our goal. Amongst the rest, one can modify the desired speed, the time headway and so on. However, working at a generic level, we choose to vary the newly introduced parameter to the framework, the cognitive capacity of the drivers. As we also elaborate, Task Capacity accommodates all the physiological and constitutional characteristics of the driver. Thus, the net outcome which is a scalar value it is assumed to describe the concept of the heterogeneity. That being said, we propose the following hypothesis:

- H_{0R}^{H} : Heterogeneity, in terms of task capacity (TC), does not induce any changes to the aggregate behaviour.
- H_{1R}^{H} : Heterogeneity affects the performance of the traffic stream.

The first set of scenarios namely H_{0R}^{VD},H_{1R}^{VD} regards the impact of the rain conditions to the vehicle kinematics (performance). It is evident from Chapter 3 that the friction coefficient affects substantially the performance of the vehicle in terms of maximum acceleration, deceleration and desired headway. As a consequence, it is expected that this degradation of the vehicle performance will exert some impact on the interactions between the vehicles. It is obvious, that an obstruction of a small bottleneck is vital to understand and quantify the impaired performance of the traffic.

The second set of scenarios H_{0R}^{RT}, $H_{1R.^{T}RT}$ is the mechanism of the decreased SA through the introduction of the induced task difficulty. The first hypothesis we make is that the weather phenomena induce an additional difficulty to the tasks. For a successful execution of the task (s), drivers need to allocate more mental resources. Following this reasoning, we allow the situation awareness, and especially the level 2 of perception to degrade. This degradation is accompanied by other two effects, the increase in reaction times and the larger and proportional biases to the stimuli. In the proposed scenarios, we allow each mechanism we described to work on its own and next we combine them in another scenario to obtain the net results.

Thereafter, we introduce the mechanism of behavioural adaptation of the drivers which is an alleviating mechanism of the risk that is created from both adverse weather conditions and this small perturbation. In the following table the scenarios that we experiment with are illustrated. We highlight that not all the combinations of scenarios are considered as some combinations give irrational basis. For instance, a scenario that does not consider perceptual biases while considers behavioural adaptation is illogical.

Accordingly, for the case of fog we make the following hypotheses. The first hypothesis we make is that the fog induces additional task demand to the preforming car following task:

- H_{0F}^{ITD} : Fog does not induces any task demand to the performing task(s) of car following.
- H_{1F}^{ITD} : Alternative hypothesis is true.

That being said, the next mechanism is to allow the mechanism of the reaction time, which is formally introduced as:

- H_{0F}^{RT} : Reaction time does not affect the performance of the traffic stream.
- H_{1F}^{RT} : Alternative hypothesis accepted.

Another effect of foggy conditions is that fundamentally altered the perception of the distances. In Section **??** we discussed that foggy conditions make the driving population to follow an exponential decay relationship w.r.t. the distance estimation. Normally, it is derived from empirical observations that, by and large, drivers has a propensity of underestimate the distances under normal driving conditions. With regards to the speed estimation, research indicates, so far, that the drivers suffer from overestimation. The most solid argumentation is placed upon the fact of the mutilation of the visual cues. We propose the following hypothesis:

- H_{0F}^{PQ} : Fog does not exert perceptual biases to the drivers with regards to the distance and speed perception.
- H_{1F}^{PQ} : Alternative hypothesis stands.

Remark: While the perception errors defined by SA mechanism, we choose to only to influence the perception errors of speed as no empirical relationship is defined until this point and exacerbate the already distorted distance estimation.

For the behavioural adaptation mechanism we highlight that the literature gives a plethora of conclusions, always subjected to the the parameters of the experiment or the nature of the observations. This conclusion derived from literature review in Sections 5.1. As the allostasis theory postulates, drivers dynamically regulate their perceived risk by adapting the control parameters of time headway or/and desired speed at a tactical level. According to this theory we propose the following hypothesis:

- H_{0F}^{AD} : Drivers do not follow any adaptation strategy at a tactical level under the exposure on foggy conditions.
- H_{1F}^{AD} : Alternative hypothesis stands.

As we did before, we capture the inter-driver differences by modelling the concept of heterogeneity. We effectively vary the cognitive state parameter of capacity and propose the following hypothesis:

- H_{0F}^{H} : Heterogeneity, in terms of task capacity (TC), does not induce any change to the aggregate behaviour.
- H_{1F}^{H} : Heterogeneity affects the performance of the traffic stream.

4.1.3 Key performance Indicators

Key performance indicators (KPI) are measures that define the course of a study and help the process of decision - making. Firstly, they define the analytical objective of the simulations in a form of statistical measures such as means or standard deviations. Secondly, they quantify the performance of the study in terms of efficiency and safety. Thirdly, is of pivotal importance when drawing conclusions and implications. Here, we will discuss about two types of indicators, those who regard the performance of the traffic at an aggregate level and those at a disaggregate level. We propose the following KPIs:

- **Cognitive State Parameters (CSP)** : With the definition of **CSP** we refer to the state variables that we have introduced to the framework so as to define and trace the cognitive state of a driver into the simulation experiment; these parameters are the task demands TD, the task saturation TS, the situation awareness SA and the reaction time τ of a driver. For individual vehicles, we highlight their trajectory with a red line within the trajectory plot diagram to trace and explain their behaviour in conditions of free flow and when run into a small perturbation, with and without the then influence of adverse weather. We can also conclude to what extent the weather conditions or/and traffic conditions influence their behaviour.

- **Fundamental Diagrams (FD)** : The FD describe the traffic flow in equilibrium conditions. These conditions ideally are achieved when all the drivers having a headway that matches the speed. The FD is plotted in the speed-density plane or the speed - flow plane or in a flow - density plane. In the first representation, one can observe the negative correlation between speed and density. As the density increases, the speed is decreasing. In the second representation, one can see the congested and the uncongested branch. In the last representation, and the most frequently used, one can see the two states of the traffic; that is congested and uncongested. It is evident, that the empirical FD has a scatter on the observations due to the inter-driver and intra-driver differences. Although that FD's are used to show equilibrium conditions, here are used mainly as a cross-validation of the underlying theory. These differences collectively referred to as heterogeneity. This simple but rather powerful representation is important to cross-validate the results of a simulation study in the absence of any empirical data. For instance, we can give an intuitive example. If the vehicles speed are high for low-density conditions (free flow) and higher than the speed limit of the road segment, then a fallacy lies in the modelling logic. This simple example and interpretation boil down the rationale of face - validation.

- **Trajectories** : Trajectory is a graphical representation of x(t) in a plane (t,x). Vehicle trajectories is the most complete measure that provides all the information about the state of a road segment. Trajectories will provide us information regarding traffic patterns produced in the simulations. By this way, we can draw conclusions regarding the plausibility of the patterns, given the circumstances and irregular aggregate behaviour. In addition, with the trajectories, the following indicators can be estimated.

- **Total Time Spent (TTS)** : The TTS is the network is defined as the summation of the travel time of all the vehicles, to reach from their origin (O) to their destination (D). This KPI indicate the efficiency of the network. The following equation used to estimate the TTS:

$$TTS = \sum_{i=1}^{N}(t_i^D - t_i^O) \tag{4.4}$$

  where TTS is the total time spent in the network expressed in hours [h] or minutes [min], t_i^D is the time stamp of the vehicle that enters the network, and t_i^O the time stamp that the vehicle reaches its destination. N is the total number of the vehicles for the whole simulation period.In the present case, the information of the travel time of each vehicle is directly available at any time from the trajectories. The TTS in this study is estimated within the area Ω as seen in Figure 5.28. Thus the TTS_{Edie} is calculated as follows:

$$TTS_{Edie} = \sum_{i=1}^{n} |(min(t_i(x_{min}), t_{min}) - max(t_i(x_{max}), t_{max}))| \tag{4.5}$$

  where t_{min}, t_{max}, x_{min}, x_{max} are the spatio-temporal coordinates that define area Ω.

- **Total Distance Covered (TDC)**: Due to the nature of the experiment, it is possible to know at any instant all the information regarding the trajectories of the vehicles. For this reason we can easily derive the total distance covered from the simple segment.

$$TDC = \sum_{i=1}^{N}(x_i^{end} - x_i^{start}), \forall i \exists S \tag{4.6}$$

where S is the set of vehicles that either successfully finished the simulation or are active in the simulation network. Again, we prefer to calculate the TDC in the predefined area Ω as follows:

$$TDC_{Edie} = \sum_{i=1}^{n} |(min(x_i(t_{min}), x_{min}) - max(x_i(t_{max}), x_{max}))| \tag{4.7}$$

where t_{min}, t_{max}, x_{min}, x_{max} are the spatio-temporal coordinates that define area Ω.

- **Time to Collision (TTC)** : TTC measures the time between two vehicles, i and i-1, given their speed and trajectory remain the same. The mathematical formulation between the follower and its predecessor is given below:

$$TTC_i = \frac{s_i}{v_i - v_{i-1}} \tag{4.8}$$

where t_{min}, t_{max}, x_{min}, x_{max} are the spatio-temporal coordinates that define area Ω. for every vehicle i that the speed is higher than its predecessor i-1, $Dv_{i,i-1} > 0$.

- **Number of Accidents (NoA)** : The last measure to indicate the safety of the simulation is the measure of the total number of collisions, if any.

4.1.4 Edie's Generalised definitions

We apply Edie's Generalised definitions to calculate the flow (q), density (k), and speed (v) of a predefined area $|\Omega|$ since the trajectories of all vehicles in the simulation are known. According to Edie, one can calculate the flow by dividing the TDC as defined in Equation 4.7 by the total area of space - time $|\Omega|$:

$$q = \frac{TDC}{|\Omega|} \tag{4.9}$$

Following the same rationale, one can calculate the density by dividing the TTT, equation 4.5 by the area $|\Omega|$:

$$q = \frac{TTS}{|\Omega|} \tag{4.10}$$

Lastly, the speed can be calculated using the fundamental relationship in traffic flow:

$$v = \frac{q}{k} \tag{4.11}$$

The area omega has temporal coordinates t_{min} =100 [s], t_{max} =750 [s] and spatial coordinates x_{min} =0.5 [km], x_{max} =4.5 [km] and it is illustrated on x-t plane in Figure 5.28 with yellow hatched color.

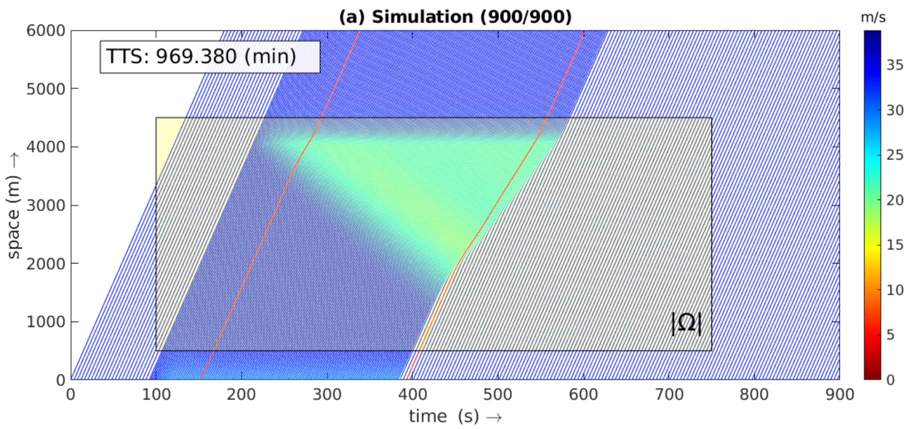


Figure 4.4: Edie's Generalized Definitions, Area $|\Omega|$

4.1.5 Scenarios for the case of rain and fog

In this section, the scenarios to be conducted for the cases of rain and fog are illustrated in the tables 4.2 and 4.3 respectively. For the case of rain, we come up with 9 scenarios that each of which represents the impact of each mechanism in an additional impact. For instance, the first scenario fo rain in table 4.2 assess the influence of the change in vehicle kinematics and scenario 3 e.g. studies the influence not only on the mechanical characteristics but also perceptual mechanisms of the induced task demand on reaction time and on the perception of speed. By following this way, we arrive at scenario 9 in which all the (assumed) mechanisms working together to produce behaviour under rainy conditions. In this part, we highlight that the direction of bias of perception errors of drivers is rather unclear, thus the scenarios 3,4 are carried out one time with the preferred bias pointing towards overestimation and on time towards overestimation. However, in both cases we let room for a scant portion of the opposite bias than the prevail one. To the ensuing scenarios we assume that the dominant bias without any strong evidence to be the underestimation having a proportion of 25 % to the overestimation.

Table 4.2: Scenarios to be conducted for the case of rain

	MVD	ITD	RT	PE v	PE s	BA v_0	BA T	H
Scenario 1	x							
Scenario 2	x	x	x					
Scenario 3	x	x	x	x				
Scenario 4	x	x	x		x			
Scenario 5	x	x	x	x	x			
Scenario 6	x	x	x	x	x	x		
Scenario 7	x	x	x	x	x		x	
Scenario 8	x	x	x	x	x	x	x	
Scenario 9	x	x	x	x	x	x	x	x

Similarly to the case of rain we set up the scenarios for the case of foggy conditions. Here we distinguish 7 scenarios that can be seen in table 4.3. The first scenario investigates the influence of the high task demand on the reaction time and thereafter, one-at-a-time we assess the impacts of the cognitive/physiological mechanisms on the disaggregate and collective behaviour. It is worth highlighting that the perception of distances are governed by a power-law form relationship while for the case of speed estimation the bias has propensity towards overestimation. After the investigation of the possible cognitive mechanisms to the scenarios 3-5 we end up to the last scenario that assess all the cognitive mechanisms by let them working simultaneously.

Table 4.3: Scenarios to be conducted for the case of fog

	ITD	RT	PE v	PE s	BA vo	H
Scenario 1	x					
Scenario 2	x	x				
Scenario 3	x	x	x			
Scenario 4	x	x		x		
Scenario 5	x	x	x	x		
Scenario 6	x	x	x	x	x	
Scenario 7	x	x	x	x	x	x

4.1.6 Sub - Conclusions

This section encloses the design of experiments. We firstly introduce the experiment with all the corresponding parameters. Thereafter, we illustrate the methodology with which the "virtual" - flow conserving - bottleneck is introduced to the experiments so as the vehicles within the simulation interact with each other. Most importantly, the hypotheses are formed and the corresponding scenarios are illustrated as well. To asses the performance of the of the simulation in terms of efficiency and safety several key performance indicators were illustrated.

1. What indicators can be used to assess the aforementioned dimensions of performance?

   In the previous section we went through a deep analysis of what Key Performance Indicators can be used in order to assess the performance of the network in term of efficiency and safety. For the assessment of the cognitive state of the drivers we choose to plot the state-variables of SA and TD. Accordingly, to assess the performance of the road segment is chosen the TTS as a predominant measure. The validation of the response of the model is consulted by the trajectories and the plots of the fundamental diagrams. Safety is judged by looking at the TTC and the number of accidents. Additional performance measures are derived by making use Edies generalised definitions.

5 RESULTS AND DISCUSSION

This chapter contains the results of the main investigation of the conceptual framework that has been proposed. Both conceptual frameworks of rain and fog are partitioned with respect to the hypotheses formulated in the previous chapter executing the scenarios proposed in table .. and the results of each case presented and further elaborated. In every subsequent simulation we conduct in addition to the base case, the mechanisms are additive to the previous. Therefore, the final simulation of each conceptual framework combines all the proposed mechanisms.

5.1 BASE CASE – CALIBRATION

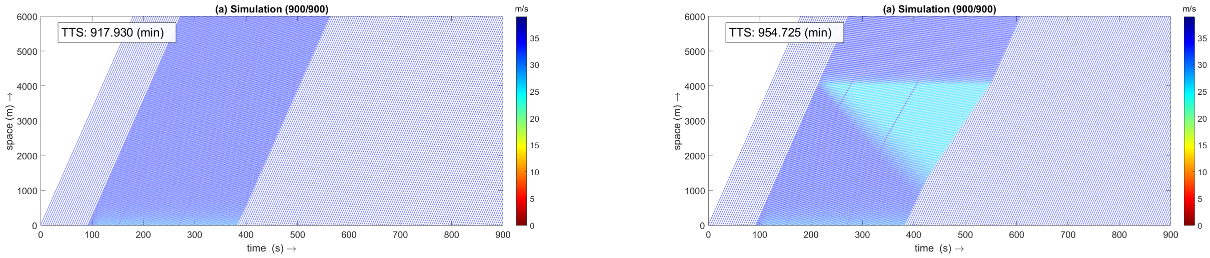
This section aims to define the base case scenario which is a reference to compare against all the rest of scenarios when using the mechanisms to generate and explain the driving behaviour during rain and fog. To define a meaningful scenario we start by:

- Applying the geometry of the road segment as proposed in Table 4.1.
- For the kinematics we use the longitudinal model of IDM+ with parameter values as illustrated in Table B.2.
- Performing a first scenario with **no** disturbance and a second **with** a disturbance as we propose in section 4.1.1.
- Using the proposed formulation in section C.4 regard the vehicle kinematics and investigate the performance of the simulation whether is comparable with the IDM+ or can potentially generate trivial results. In the case that the proposed formulation is not desirable we perform a fine-tuning of the parameters until we attain desired performance in terms of TTS. Otherwise, we continue carrying on the rest of the proposed scenarios.

Initially, we run a simulation by using the IDM+ model. The produced trajectories are illustrated in Figure 5.1. The performance of the road system is measured with Total Time Spent (TTS). Under free flow conditions, the performance of the network is TTS = 917.932 min. Under undisturbed conditions, the vehicles are traversing free the road segment at their desired speed, which is the speed limit of the road segment. When the bottleneck is set in place, the performance of the network, as expected, deteriorates to TTS = 954 min. At the location of 4 [km] the perturbation of the bottleneck starts propagating backwards. The vehicles one after one start breaking in order to regulate their velocity accordingly. From this bottleneck, the wave speed that propagates backwards can be easily calculated and it has value of $w_s = 18.46$ [km/h]. The aggregate behaviour, as expected, reassembles to a great extent to the pattern that illustrated previously in Figure 4.3(a). In the absence of any other stochastic process, the The bottleneck creates a homogeneous pattern of congestion to the upstream of the road segment.

The next step is to simulate the base case with the extended equations proposed in Chapter 3 with parameter values that of Appendix B. We aim to produce the ”same” behaviour as we did with the IDM+. By doing so, we are certain that the model behaviour, aggregate and disaggregate, is desirable while reliable to include additional cognitive mechanisms, and perform comparisons against the rest scenarios. That said, at the end we can draw draw meaningful conclusions about the methodological part.

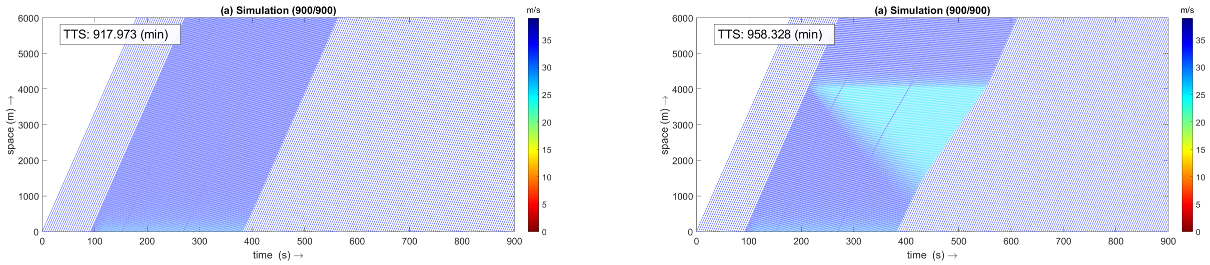
After conducting the experiment with the extended equations, the produced trajectories are shown in figure 5.6. For the case with no disturbance, the TTS is 917.973 min which is identical with the base case of IDM+. With



(a) Base case scenario, no disturbance

(b) Base case scenario, with disturbance

Figure 5.1: Trajectories produced with IDM+ and emergent traffic patterns



(a) Base case scenario with extended IDM+, no disturbance

(b) Base case scenario with extended IDM+, with disturbance

Figure 5.2: Trajectories produced with IDM+ and emergent traffic patterns

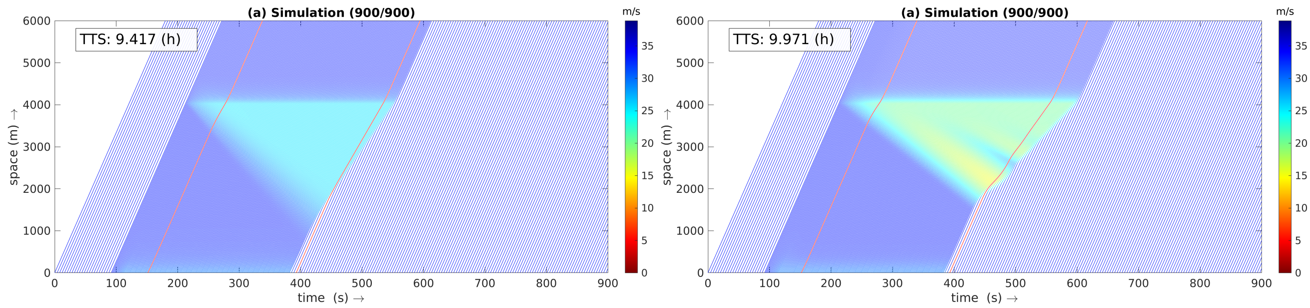
the bottleneck in place, the efficiency of the network is 958.328 [min]. We have no reason to neglect this result and thus we continue performing the proposed experiments.

5.2 SIMULATING THE MECHANISMS OF RAIN

This section investigates the mechanisms of rain that are hypothesized to affect the human behaviour and the vehicle kinematics in order to generate and explain the traffic patterns that we see at these special conditions.

5.2.1 Vehicle Performance Degradation

The first mechanism we allow to take effect on the methodological framework is the so-called vehicle performance degradation which alters the kinematic friction coefficient between the tiers and the surface of the road. This case is the one that naturally we can observe in nature. The case which is considered as "normal conditions" we use the friction coefficient as 0.6 (see reference) and the case while the rain conditions are set to 0.4. Even though that we choose to vary the intensity of the rain within the range 0.5-10.0[mm/h] which implicitly affect the visual acuity of a driver, it has no any effect as the human factors are not initiated in this simulation. Therefore, the results for the different intensity rain values is the same along the results of the simulations.
In Figure 5.6 we illustrate the emergent patterns of the traffic stream along the 15[min] of simulation of the 6km road stretch. On the vertical axis is space (location) and on the horizontal axis is the time. In figure **(a)** is an aggregate pattern that it was expected to obtain. This homogeneous behaviour concerning the disturbance indicating that the disaggregate agents (vehicles), with all the same parameters they respond exactly the same to the bottleneck. In addition, the wave that propagating backwards from the location of the bottleneck towards upstream is approximately 18 km/h, which indicates that the theory is correct about the emergent pattern. The resolution of the congested state is rational. When we allow the MVD to the model, we obtain a pattern that is similar to the first combined with small perturbation in the congested state. These perturbations can be seen in figure 5.6 **(b)** colored with yellow color. The aggregate pattern is logical to be derived as the degradation of the agility of the vehicle, with in turns affect the acceleration, yields into a timid behaviour making this small

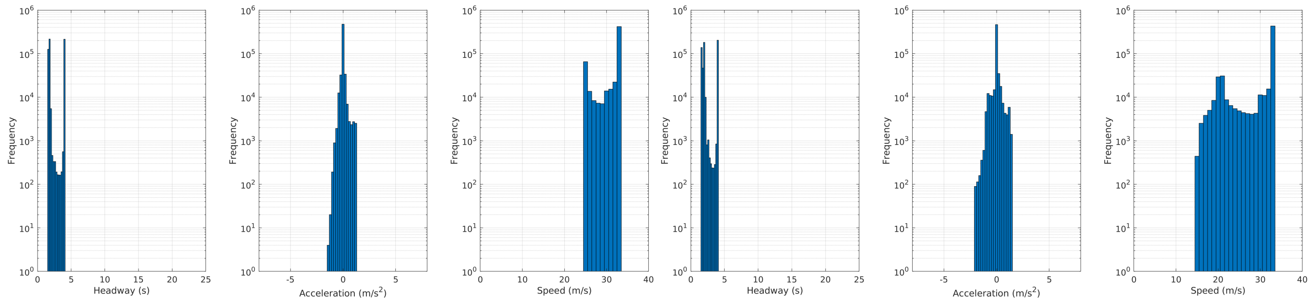


(a) ”Normal” conditions with friction coefficient 0.6

(b) Rainy conditions with friction coefficient 0.4

Figure 5.3: Emergent patterns with mechanisms of MVD

perturbations to amplify the effect to the upstream.



(a) ”Normal” conditions with friction coefficient 0.6

(b) Rainy conditions with friction coefficient 0.4

Figure 5.4: Histograms of acceleration, speed and time headway

Following that, we plot the distributions of the acceleration, speed and time headway for the vehicles in the simulation. The time headway distribution has two distinct spikes which reflect the generation frequency in which the vehicles enter the road strech; that is 900veh/h and 2200veh/h. If someone wants to exclude this additional information from the distribution can easily cut-off a sufficiently long starting distance of the road stretch. Speed distributions differ slightly with regards to the lower speeds in the case that the mechanism of MVD is in place. The large spike from at the opposite of the skewed tail is the desired speed that the vehicles inherited (”obliged”) to follow; the speed is 30m/s. For the acceleration distribution, we admit a skewness towards deceleration for the case of MVD. This is rational as the drivers prompt into more cautious,overreacting, behaviour as the infrastructure is slippery. When we looking at the fundamental diagrams of flow-density and speed-density 5.5, we arrive to the confirmation that the underlying theory that we have applied is reasonable as follows the basic patterns of traffic flow theory. The diagram **Q-K** has two distinct branches, the congested and the uncongested. At the left side we can see the uncongested state in which the data points form a line in which when calculating the first derivative we obtain the free flow speed, whereas at the right side is the congested state in which the data points are scattered. The diagram of **V-K** gives us the same information about the behaviour of the stream. In this case, we clearly see the ”policy” restriction of 120km/h that the vehicles are obligated to follow clearer as no data point is located above 120 [km/h].

Sub - Conclusions

Finally, concerning the KPI’s we have introduced, we observe a deterioration of the network in terms of TTS and mean speed of the vehicles. The deterioration of the speed is 5.5% which is in a good agreement with the empirics of other studies. The density k is higher in the case of the MVD, which means that the vehicles coming closer to each other.

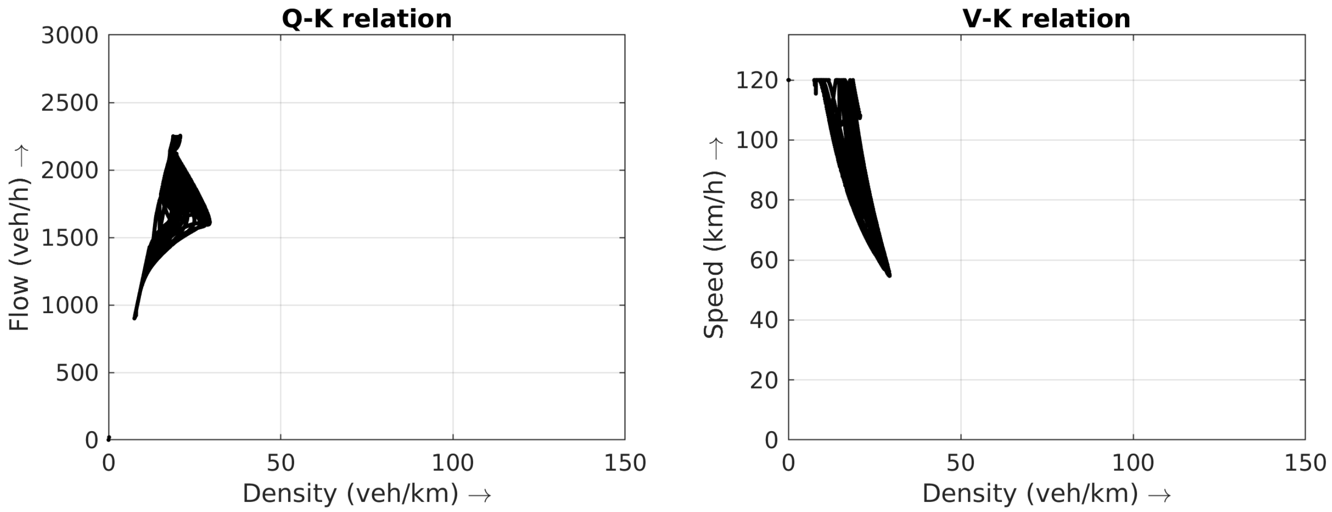


Figure 5.5: Fundamental Diagrams of flow-density and speed-density in case of MVD

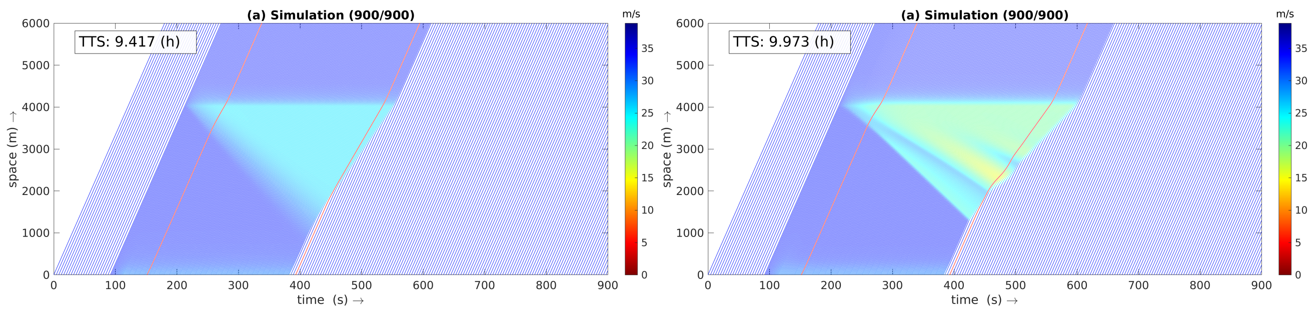
Table 5.1: KPIs

	TTS	TDC	TTC	Accidents	u	k	q
Base Case	9.417	1.05*1000	0	0	111.25	13.038	1451
MVD	9.971	1.05*1000	0	0	105.1	13.81	1451

5.2.2 Induced Task Demand

In this section we introduce the concept of induced task demand that we hypothesize to be in effect, as the drivers influenced by higher task demand for the same task of car following as the visual acuity of the drivers suffers. At first hand, we allow this induced task demand to influence the reaction time of the drivers. Following we present the results of the simulation.

Reaction Time



(a) "Normal" conditions

(b) Rainy conditions (10.0mm/h)

Figure 5.6: Emergent patterns with mechanisms MVD+ITD+RT

Regarding the human factor state variables we choose to analyse two vehicles, the one is generated into high demand conditions, that is the **veh 60** and the second one is the **veh 200** which is generated right after the high demand period. Starting from figure 5.7 **(b)** we admit that the SA of the driver is degraded for the whole road segment beside the time that runs into the shock-wave whereas reducing the speed and thus the SA is improved with the highest awareness at the time that the vehicles surpass the location of bottleneck. Accordingly, the total task demand is high following a symmetric pattern to the SA function. Regarding its speed, we see that decreases when it finds interaction with other vehicles near to the location of the bottleneck while regains speed at the downstream of the bottleneck. The reaction time of the vehicle is affected proportionally of the degraded

SA having 0.1s lag from the initial reaction time we set. Looking at 5.7 **(e)**, we see the state traces of SA and total TD. In low demand conditions the SA is high and the total TD is low. By the time that the vehicle reaches the perturbations caused by the bottleneck, the SA falls and TD increases leading the vehicle to having oscillatory patterns regarding the speed and subsequently the acceleration/deceleration. Its reaction time for the whole simulation period remains intact at its initial value of 0.5s.

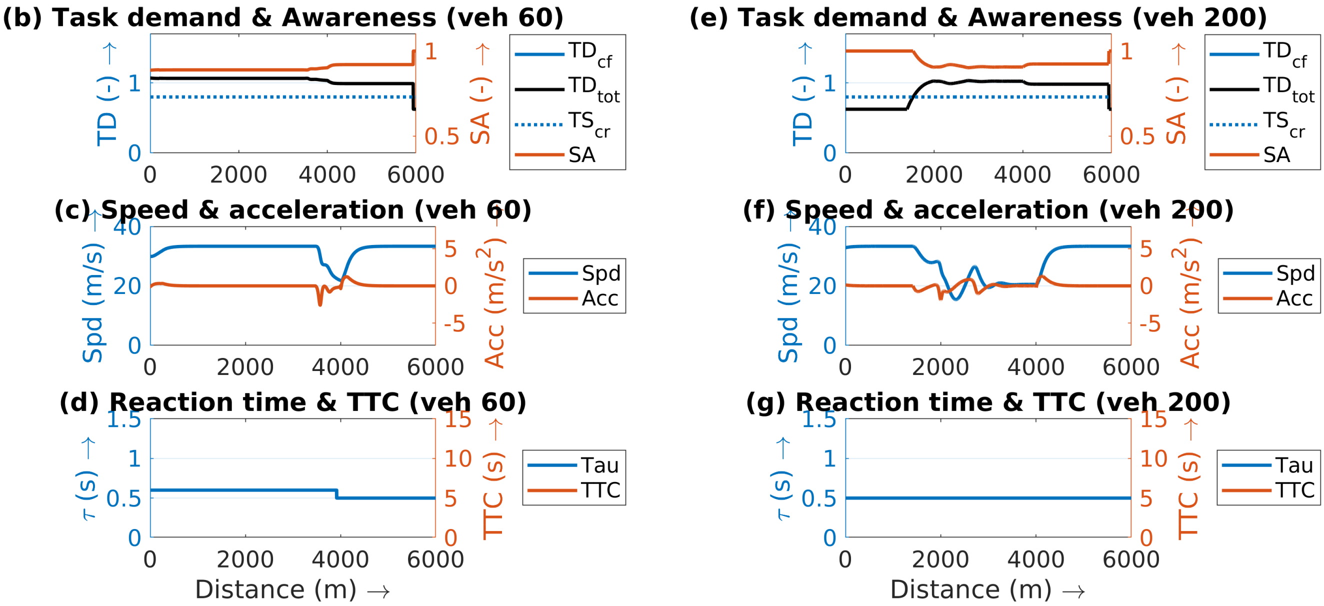


Figure 5.7: Fundamental Diagrams of flow-density and speed-density in case of RT

Figure 5.8 shows the hysteric patterns of the vehicles within the simulation. Especially for the vehicle 200 we clearly see the trajectory that starts from the uncontested branch of the FD, follows a clockwise direction within the boundaries of the FD and after the vehicles reaches the end of the bottleneck regains the position of the uncongested branch of the FD.

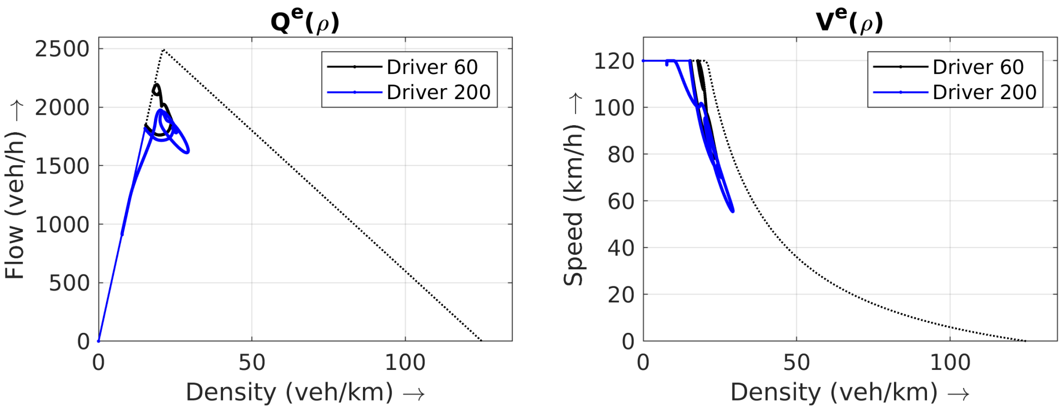


Figure 5.8: Fundamental Diagrams of flow-density and speed-density in case of RT

Sub - Conclusions

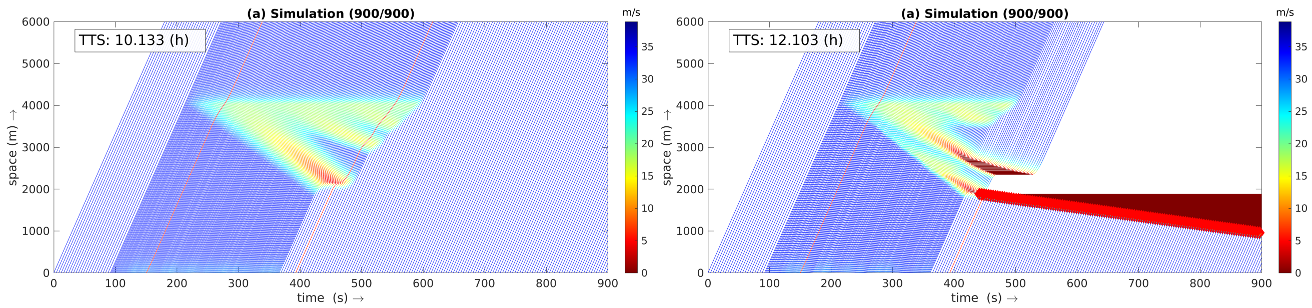
The performance indicators are amassed in the following table showing the changes between the basic conditions and the rainy conditions when we are considering the driver has basic reaction time, while the induced task demand influences the reaction time.

Table 5.2: Results

	TTS(h)	TTC(min)	Accidents	u(km/h)	k(veh/km)	q(veh/h)
Base Case	9.41	78.12	0	111.2	13.0	1451
MVD + RT (i = 0.5mm/h)	9.97	79.92	0	105.0709	13.8	1450
MVD + RT (i = 1.0mm/h)	9.97	79.92	0	105.0709	13.8	1450
MVD + RT (i = 2.0mm/h)	9.97	79.92	0	105.0709	13.8	1450
MVD + RT (i = 3.0mm/h)	9.97	79.92	0	105.0	13.8	1450
MVD + RT (i = 4.0mm/h)	9.97	79.92	0	105.0	13.8	1450
MVD + RT (i = 5.0mm/h)	9.97	79.92	0	105.0	13.8	1450
MVD + RT (i = 6.0mm/h)	9.97	79.92	0	105.0	13.8	1450
MVD + RT (i = 7.0mm/h)	9.97	79.92	0	105.0	13.8	1450
MVD + RT (i = 8.0mm/h)	9.97	79.92	0	105.0	13.8	1450
MVD + RT (i = 9.0mm/h)	9.97	79.92	0	105.0	13.8	1450
MVD + RT (i = 10.0mm/h)	9.97	79.92	0	105.0	13.8	1450

Effects on Distance Estimation (Overestimation vs Underestimation)

In this section, we discuss the results when allowing perceptual biases and especially we start by the distances overestimation. As we mentioned above, the fraction of the drivers with overestimation and underestimation is 75% to 25% respectively. The emergent patterns that resulted from the simulation can be seen in figure 5.9 showing the base case and the case that the intensity of the rain is 10.0mm/h. What is obvious by looking at these patterns is that the collective behaviour of the high-intensity conditions has an offset temporally later in time while the average speed is lower from the base case. In the case of moderate rainfall, the traffic stream is starting to oscillating with the appearance of the first moving jam moving backwards. Subsequently, the oscillations that starting from the bottleneck rear after the first moving jams are not that intense. Moreover, in the case of high-intensity rainfall, we observe higher oscillations, wherein the first moving jam triggers a chain-reaction collisions from a point around 400s until the end of the simulation. Likewise, the second moving jam influence the drivers to such an extent that they come to a stand-still position. Evaluating these patters, it can be said that the patters follow the rationale we follow for these case, i.e. the overestimation of the distances highly affect the behaviour of the traffic stream and gives a high probability of collisions. From the perspective of empirical view, this behaviour does not reflect a realistic situation as the chain-reaction collisions of is hugely unlikely to occur.



(a) Rainy conditions (7.0mm/h)

(b) Rainy conditions (10.0mm/h)

Figure 5.9: Emergent patterns with mechanisms MVD+ITD+RE+PE(distance)and biases towards overestimation

Looking at the case of high rain intensity, the state-space human factor variables are seen in figure 5.10. What is evident here and what is expected is the vehicle 200 to suffer with high levels of TD and low levels of SA. This is the case, as Evaluating the simulations by looking the fundamental diagrams we arrive to the conclusion that the underlying theory holds well as the two distinct states of congested and uncongested are clearly seen. In this particular case that the behaviour of the agents is both sluggish and overreacting the fundamental diagrams has more scattered plots as we see in figure 5.11. Substantial difference we observe when we apply bias to the distance which is empirically supported, that is a vast majority of the population of the drivers (agents) underestimate the distances. In addition, we keep a probability (small) for some drivers for overestimation. For low rain intensity, the emergent patterns show high oscillatory conditions within the effect of the induced bottleneck. A wide traffic jam starts to propagating backwards, while the traffic demand is high, whereas at the time that the forefront of the low traffic demand reaches the tail of the moving jam, has enough space to purge.

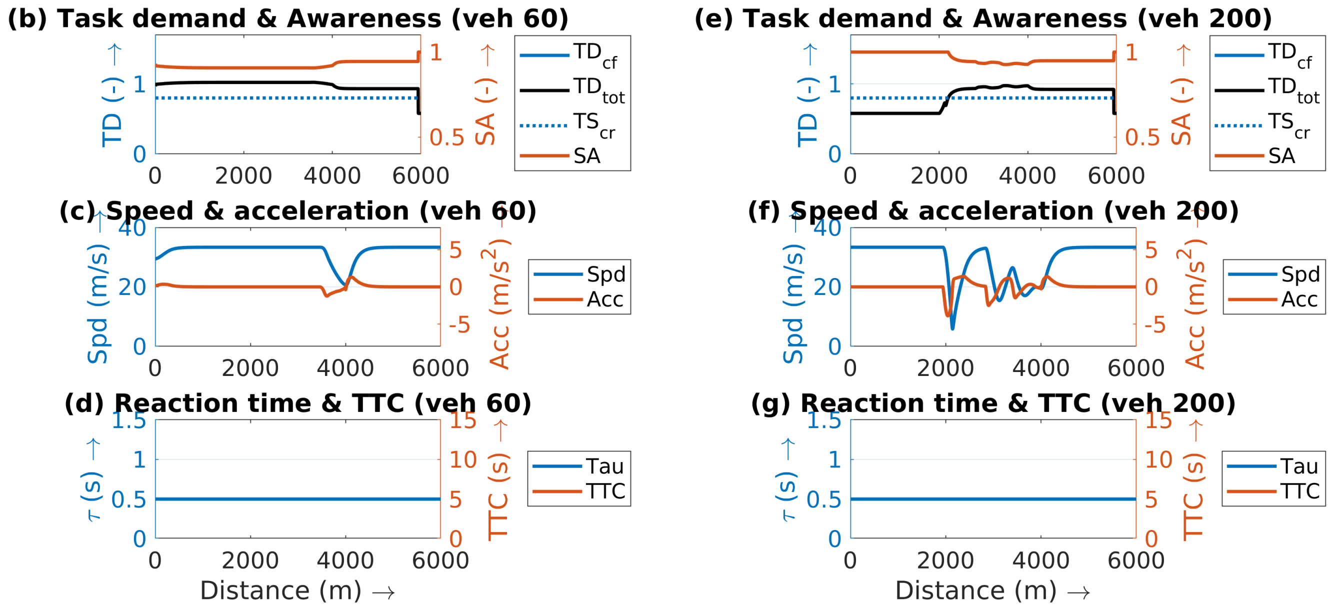


Figure 5.10: Fundamental Diagrams of flow-density and speed-density in case of overestimating the distances

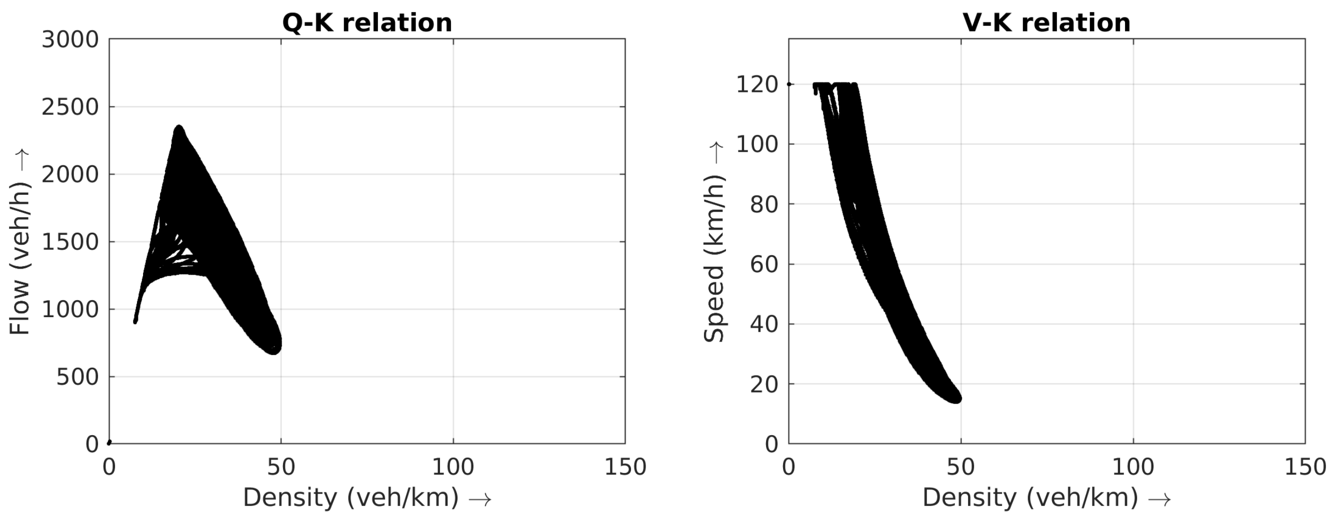
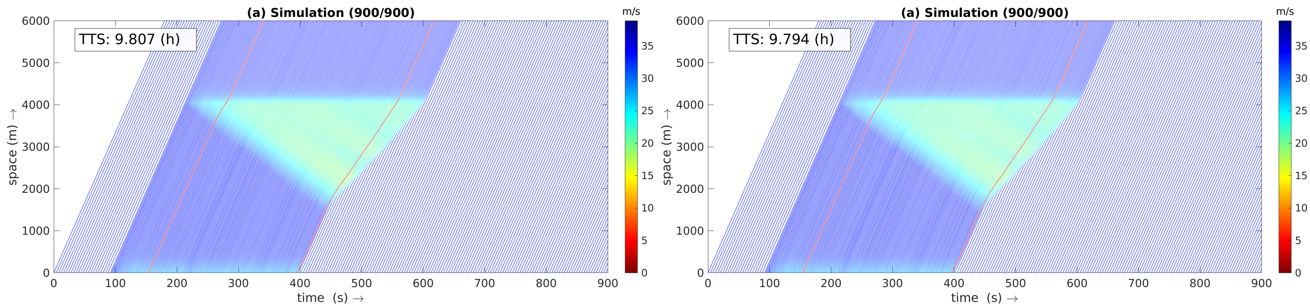


Figure 5.11: Fundamental Diagrams of flow-density and speed-density in case of overestimating distances

On the contrary, for the high rain intensity conditions, the wide moving jam triggers an incident as it can be seen from figure 5.12. This accident and the imminent chain-like incidents occured as a result of the combination of distance underestimation, the degraded friction coefficient and the suspected high task demand. The first factor of distance underestimation gave the drivers the ability to come at closer distances to their predecessors giving them no room for compensatory action(s). The second factor make impossible to make use all the deceleration "capacity" of the vehicles as the deceleration, given the influence of the environmental conditions, is restricted to -3.9m/s^2.

Sub-Conclusions

In this section we addressed the concept of distance overestimation and underestimation. We started evaluating the methodology by implementing the perceptual bias of underestimation. The 75% of the drivers overestimate the distances while we give a room of 25% for distance underestimation. This set up is rather implausible as the empirical observations lead to the conclusion that the drivers, or the vast majority of them, underestimate the distances in conditions of rain. The same applies to normal conditions. Nevertheless, it is wort seeing the results when the exact opposite is hypothesised. Remarkably, the traffic steam has a homogeneous pattern along the



(a) Rainy conditions (7.0mm/h) **(b)** Rainy conditions (10.0mm/h)

Figure 5.12: Emergent patterns with mechanism of MVD+TD+RT+PE(distance) and biases towards underestimation

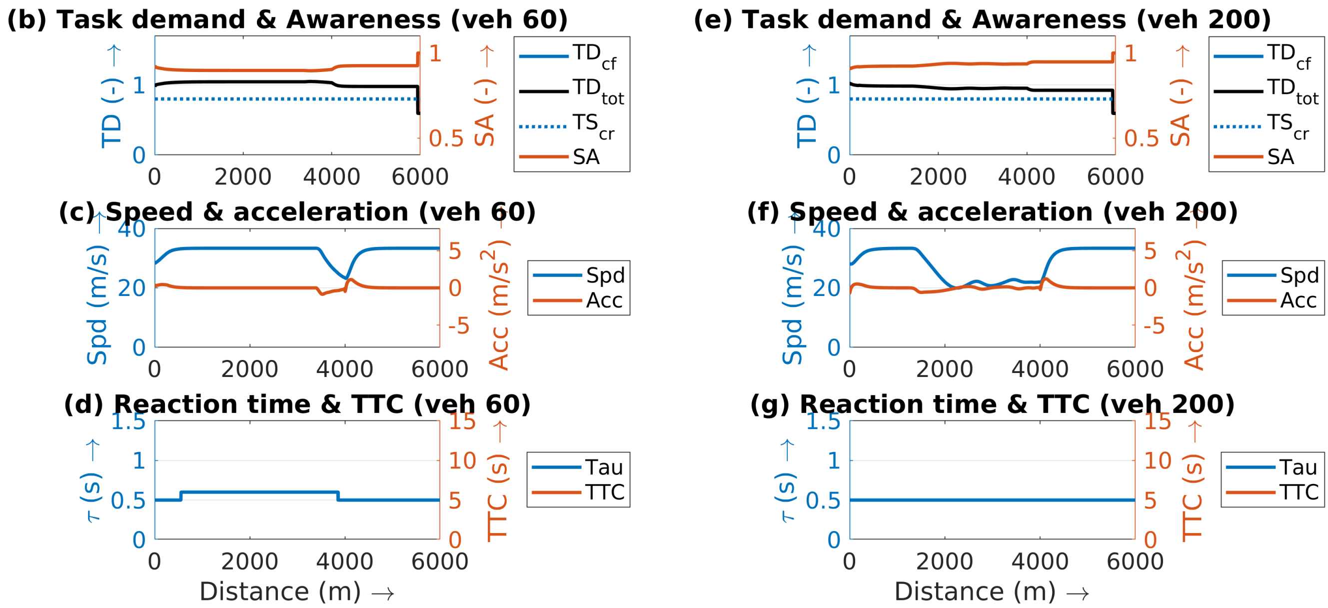


Figure 5.13: Fundamental Diagrams of flow-density and speed-density in case of underestimating distances

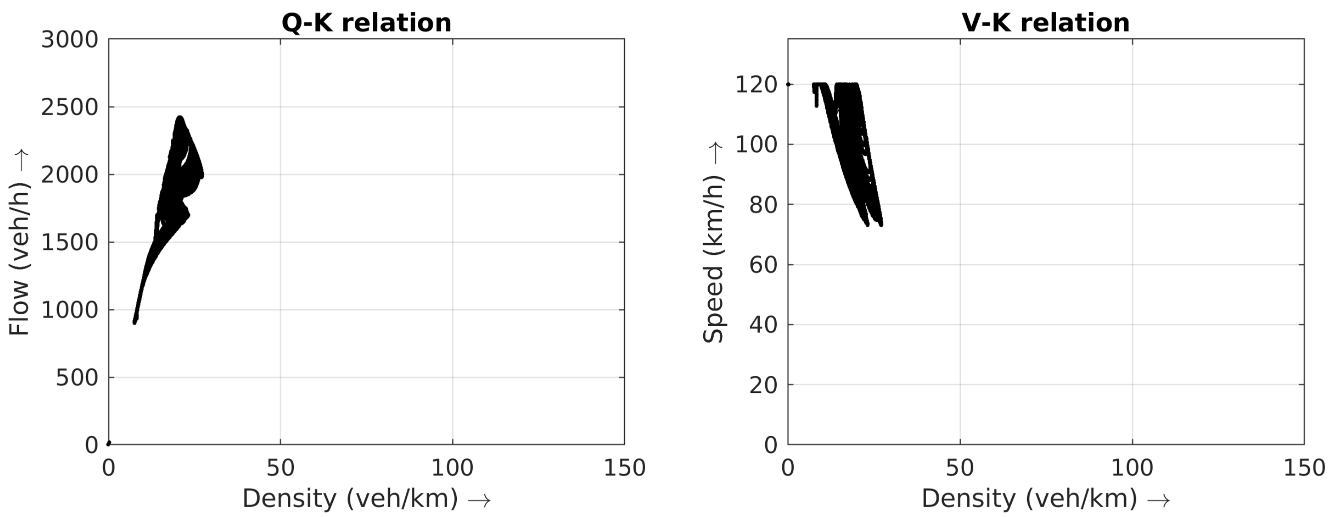
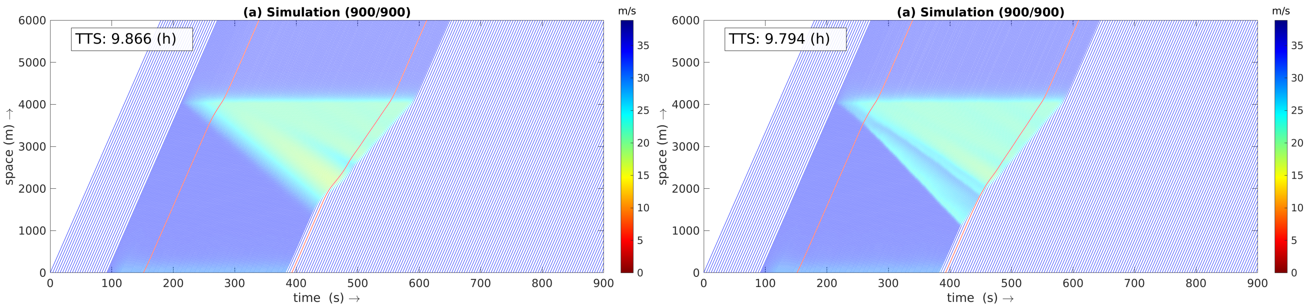


Figure 5.14: Fundamental Diagrams of flow-density and speed-density in case of overestimating distances

simulations. Hence, the distance overestimation has a functionality in favour of stability and traffic safety. This is supported by looking the figure 5.9 and figure 5.10 especially the accelerations and speed profile of vehicle 200.

Effects on Speed Estimation (Overestimation vs Underestimation)

Following the section of distance overestimation/underestimation is the section of speed overestimation. In the following part we convey the results of the simulations when the agents have a speed-propensity towards overestimation. A general remark is that the speed (differences) stimuli is not that important for this condition specific case. Unequivocally speed influences both the disaggregate and aggregate behaviour at an extend smaller than the distance stimuli for the given car-following formulation. This conclusion, however, is restricted to the model that we use in this study.



(a) Rainy conditions (6.0mm/h) **(b)** Rainy conditions (10.0mm/h)

Figure 5.15: Emergent patterns for overestimating speed

In figure 5.16 we plotted the traces of the human factors and the trajectories of speed and acceleration for the vehicles 60 and 200 in the case that the rain intensity is relatively high at 10.0mm/h. For the vehicle with id 60, the effects of speed overestimation become clear when looking at its reactions time, which is 0.1s higher than the base reaction time. This is evident as the SA is low for the largest segment of the road. At the same time, its TTD is relatively high. Nevertheless, the vehicle drives at its desired speed for the whole segment, besides the segment that comes into an interaction with the other vehicles that we admit a deceleration which leads to a speed of 20 m/s. Meanwhile, the vehicle 200 enters the segments with low traffic demand, thus the SA is high. When the vehicle 200 reaches the tail of the congested area, decelerates abruptly, as the speed is overestimated, with a resulting speed 10m/s. Thereafter, the vehicles traces an oscillatory trajectory with respect to acceleration and speed until it reaches the end of the congested area. From that point, vehicle regains its full awareness and continues travelling until the end of the simulation.

The concept of speed overestimation for the speed stimuli is somewhat hypothetical, while the reality is that the speed stimuli is usually underestimated. The previous analyses shows that the model, even with the harshest environmental conditions, is in favour of the safety and efficiency as the TTS is competent with the base case. On the contrary when we set the expected bias of speed we obtain the following results as can be seen in figure 5.17.

Effects on Perception Errors (Both Distance and Speed)

When it comes to a pragmatic driving experience, it is more logical to assume that both of the stimuli of distance and speed to being affected by the cognitive loading. When we inherit the driving population with such perception "mutilations" we can obtain traffic patterns as showed in figure 5.18. It is obvious that the bias towards underestimation is in favour of the driving performance. Even in the most severe case of rain intensity of 10.0 mm/h we observe that the traffic flow is being affected by the location of the bottleneck and the interaction at the upstream seems to smooth out due to the unintended cautious driving behaviour. With regards to the performance indicator of TTS we cannot allegate that changes significantly as the difference between moderate and high intensity rainfall is 0.08[h].

At figure 5.19 we obtain the human factor state variables of the vehicles 60 and 200. The only interesting thing to point out in this is the reaction time of the vehicle 60 that is 0.1s larger than the physical reaction time. This

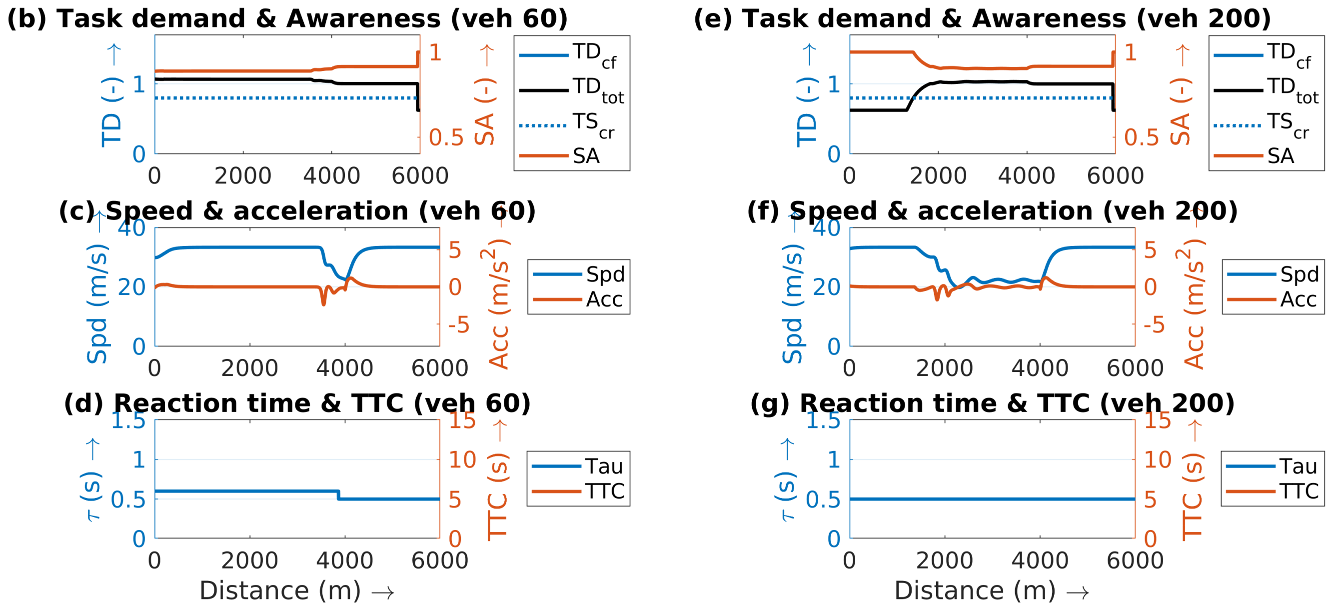
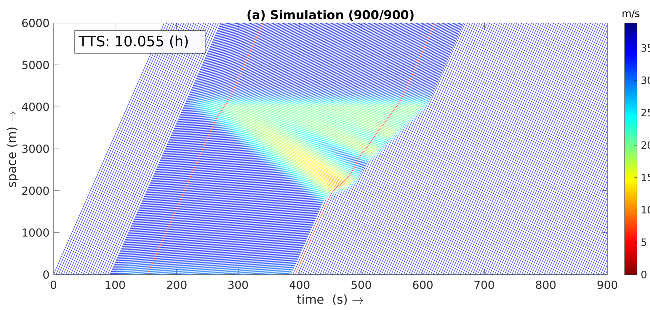
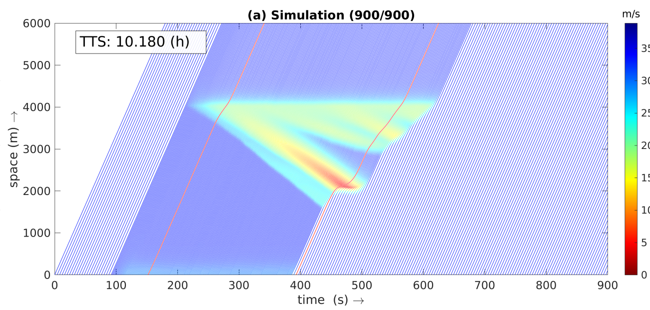


Figure 5.16: Human factors for the vehicles 60 and 200 when intensity is 10.0mm/h

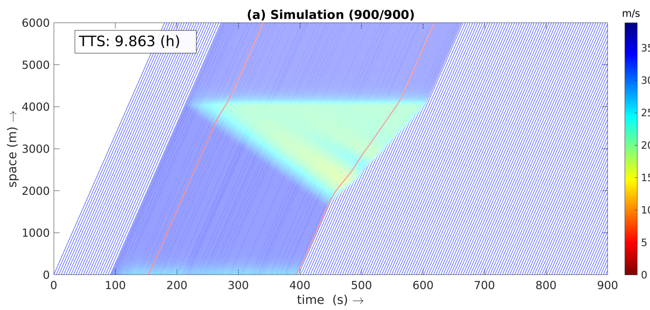


(a) Rainy conditions (6.0mm/h)

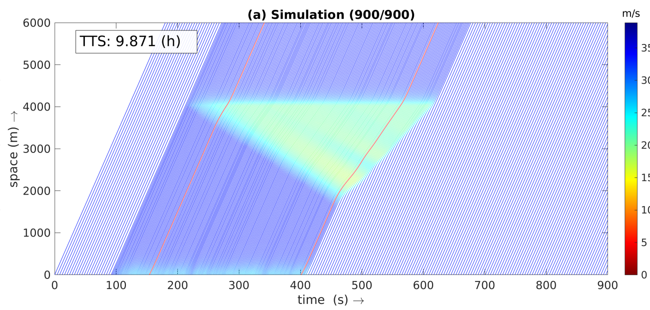


(b) Rainy conditions (10.0mm/h)

Figure 5.17: Emergent patterns emergent patterns with mechanisms MVD+ITD+RT+PE(speed) and biases towards underestimation



(a) Rainy conditions (5.0mm/h)



(b) Rainy conditions (10.0mm/h)

Figure 5.18: Emergent patterns the mechanisms of perception errors an biases to underestimation

result is very likely to be created by the manner in which the vehicles enter the simulation rather than the effect of the rain intensity. At this point we illustrate how intuitive are the biases when considering the interaction

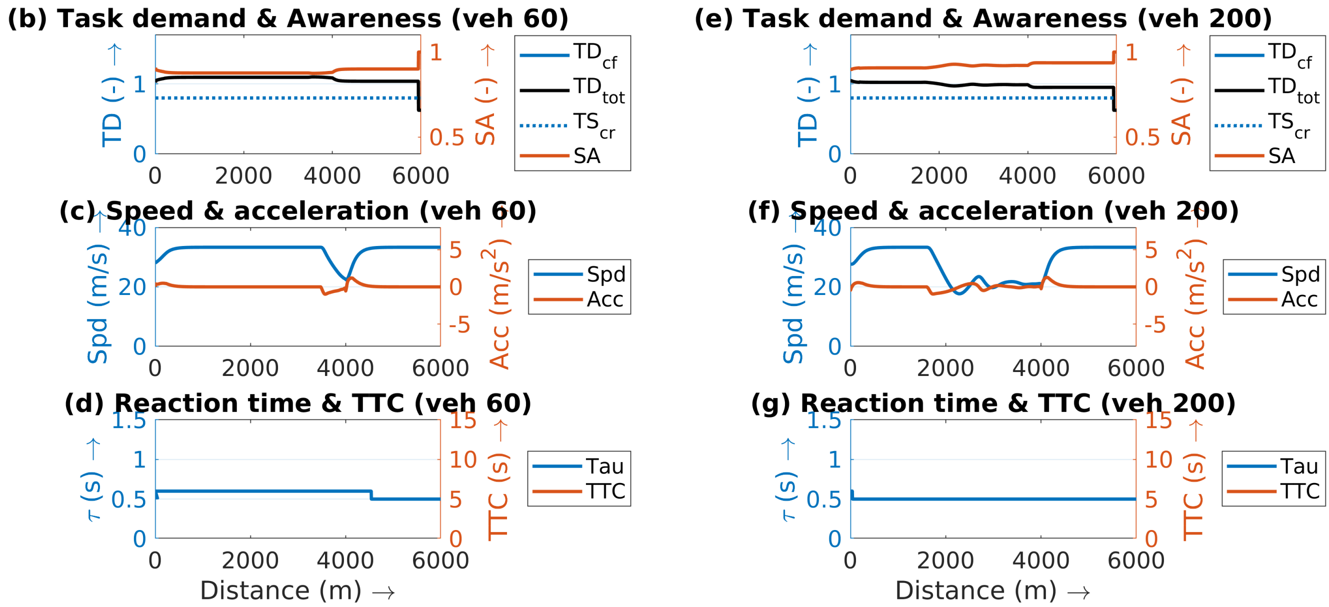
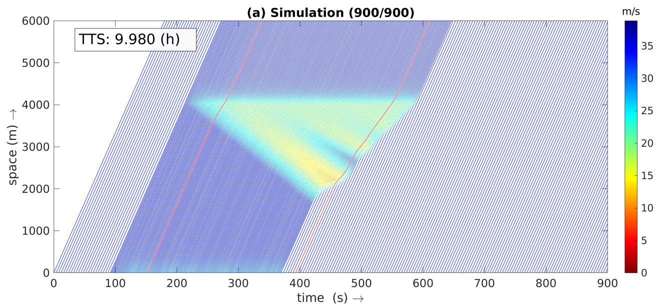


Figure 5.19: Fundamental Diagrams of flow-density and speed-density in case of PEV overestimating the distances

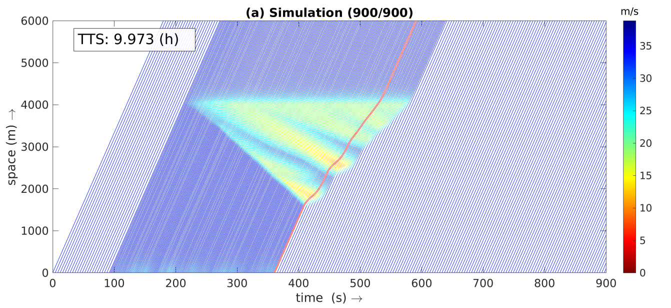
term of IDM+ model. When substituting the linear relationships of stimuli 3.26, 3.27 to the interaction term $1-(s_i^*/s_i)^2$ of IDM+, we obtain the following expression:

$$1-\left(\frac{s_0+u_n*T+\frac{u_n*(1+\delta*\epsilon_i^{SA})*\Delta u_i}{\sqrt{a_{max}*b_{comf}}}}{(1+\delta*\epsilon_i^{SA})*s_i}\right)^2 \tag{5.1}$$

we immediately observe why the biases of the distance have a greater impact on the acceleration rather than the biases on the speed. The differences in speed affect the numerator of the previous expression makes it have less influence on the final acceleration and imminently on the stability of the traffic stream. The differences in the distance though make the model more "unstable" as the parameter resides at the denominator. That is the reason why in the previous simulation cases when we investigated the perception errors one-at-a-time the influence of perceived distance yielded to higher oscillations in moderate rain conditions and accidents for the extreme cases. Another noteworthy remark is that these biases and the final influence on the traffic stream are subjected to the model of IDM+. There are not limited to a model, but the model per-se imposes a limitation due to the mathematical formulation. For instance, by taking other microscopic kinematic models, e.g Gipps car-following model, we can effectively have different results, or at least, the influence of biases to be less prominent.
When imposing to the model the unlikely dominant bias of the overestimation, the individual and the aggregate behaviour become aggressive and unstable. Looking at figure 5.20, the traffic patterns change considerably than the pattern we investigate before. For the case with the moderate rain intensity, the changes with regards to the network performance is not significant. In the case of high rain intensity though, the TTS is increased by 0.102 [h] and the traffic congestion with the combination of such a high rain intensity - cognitive loading, creates stop-and-go waves. These patters are discerned in figure 5.20-b.
We plot the human factors and the related vehicles kinematic parameters at figure 5.21-(b,g) for two successive vehicles with id 191,192. It is evident from plots c,f that the vehicles react according to the stimuli perceive by tracing along the road segment sinusoidal-type of speed and acceleration trajectory. This wave-type oscillation has a wavelength of, approximately 1 [km] with amplifying tendency. Within the bottleneck location, the oscillations are not prominent, while we are travelling to the upstream the oscillations amplified. Regarding the human factor, both drivers seem to suffer from high TD and low situation awareness. By the moment the vehicles run into the congestion waves, and due to the corrective actions, the SA is constantly above the TD allowing them to be more aware of their environment. The reaction times of the drivers have a similar oscillatory pattern, but within the bottleneck, the reaction time is increased by 0.1s.



(a) Rainy conditions (5.0mm/h)



(b) Rainy conditions (10.0mm/h)

Figure 5.20: Emergent patterns with the mechanisms of perception errors and biases to overestimation

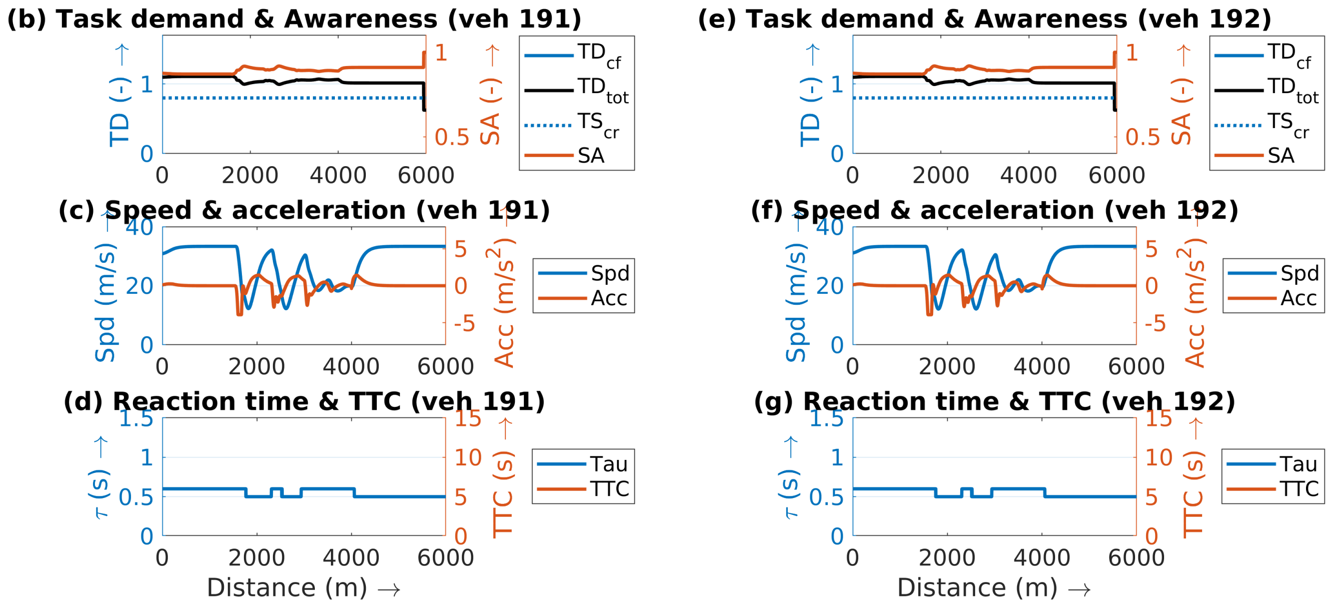


Figure 5.21: Fundamental Diagrams of flow-density and speed-density in case of PEV overestimating the distances

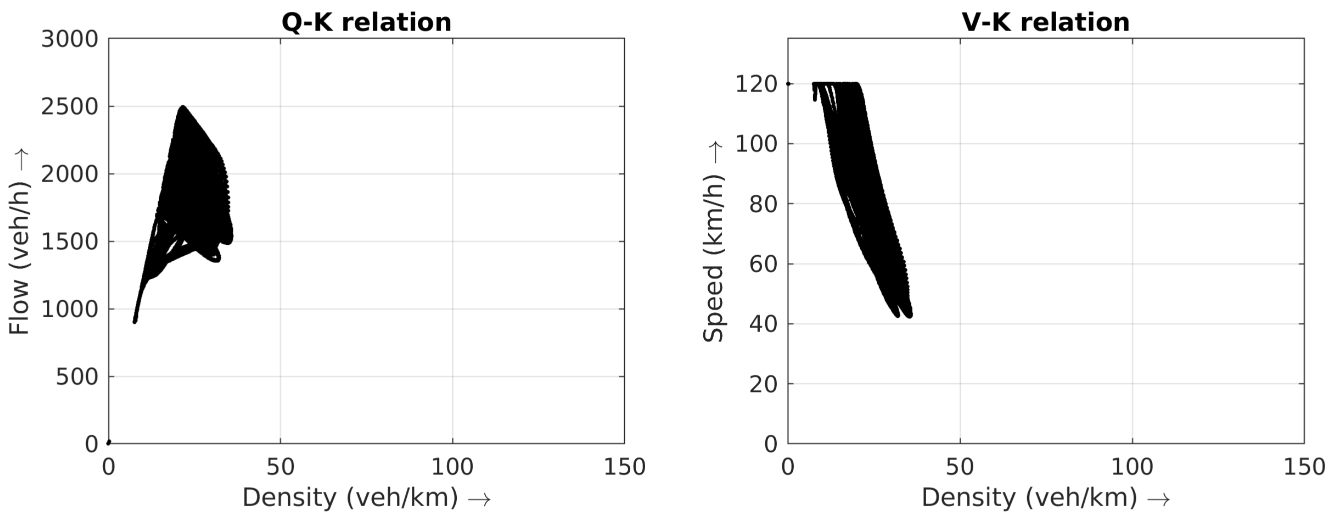


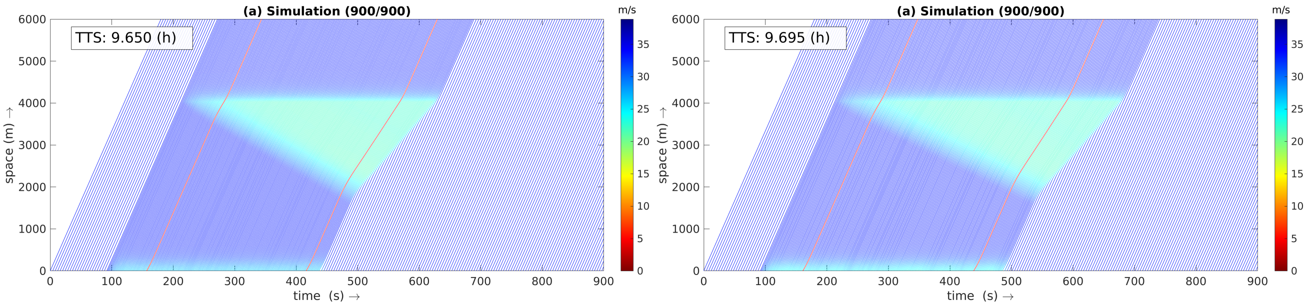
Figure 5.22: Fundamental Diagrams of flow-density and speed-density in case of overestimating distances

5.2.3 Behavioural Adaptation

In this section we present the results as derived from the simulation when introduced the concept of behavioural adaptation. Firstly, we look at the results when the behavioural adaptation of time headways is in effect, secondly when the desired speed is changing and then we look when both speed and headway are applied to the model.

Adaptation of Headway (Time)

Again, we obtain the results for moderate and high intensity rain in figure 5.23. It is clear that the effects of the time headway adaptation yields to a homogeneous congested traffic (HCT) to the upstream of the bottleneck location for the both cases of rain intensity. The TTS in the first case is 9.650(h) while in the second case in increased slightly to 9.695(h). The adaptation to time headway concerns the interaction term of IDM+ $(1-(s_i/s_i^*)^2)$ and more specifically the desired distance of the drivers.



(a) Rainy conditions (5.0mm/h)

(b) Rainy conditions (10.0mm/h)

Figure 5.23: Emergent patterns for Behavioural Adaptation on Time headway

Figure 5.24 (b)- (g) shows the dynamics of the TD and SA for the cars 60 and 200 in the case of very intense rain conditions. The TD_{60} is around 1 and thus does not create any problem for the car to to execute its task of car following. When the same car runs into the congestion, immediately changes its speed to slower but this fact has an impact on TD and SA which are turn into low and high respectively. The same results we obtain for the car 200.

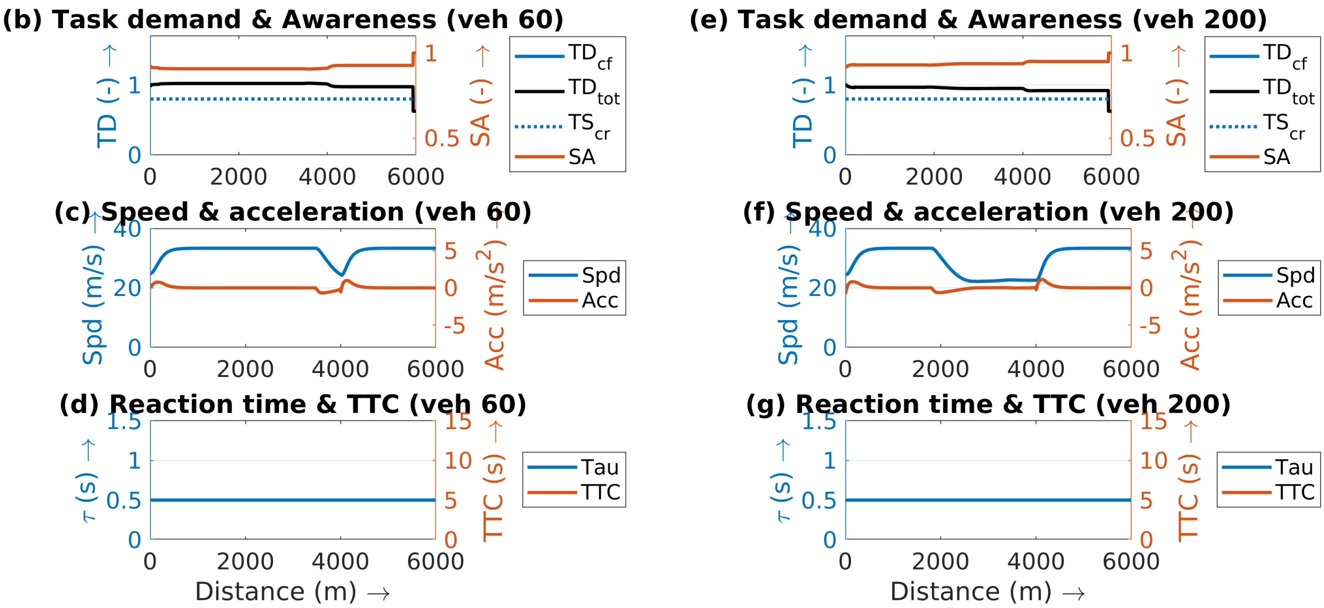
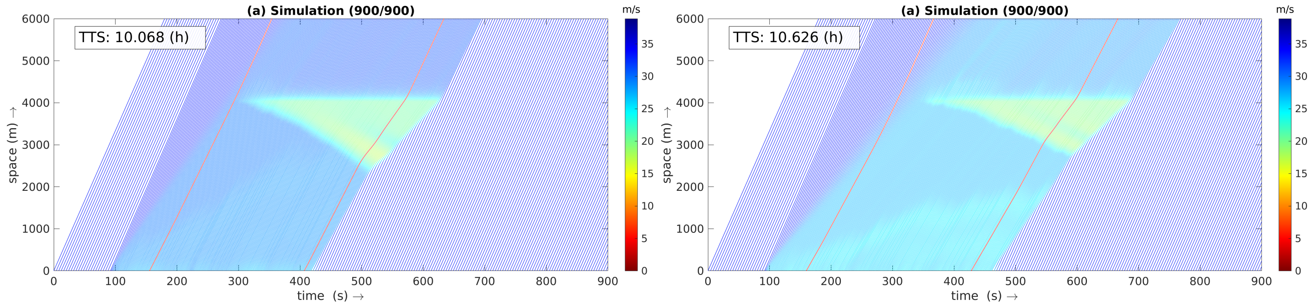


Figure 5.24: Human factors for high rain intensity (10.0 mm/h) in the case of time headway adaptation

Adaptation of Desired Speed

The adaptation to the desired speed leads to larger TTS compared to the adaptation to the desired headway scenario and also leads to less severe congestion patterns as figure 5.25. More specifically, the TTS for a medium rain intensity conditions is 10.068 [h] while for severe rain intensity is 10.626 [h].



(a) Rainy conditions (4.0mm/h) **(b)** Rainy conditions (10.0mm/h)

Figure 5.25: Emergent patterns with Behavioural Adaptation on desired speed

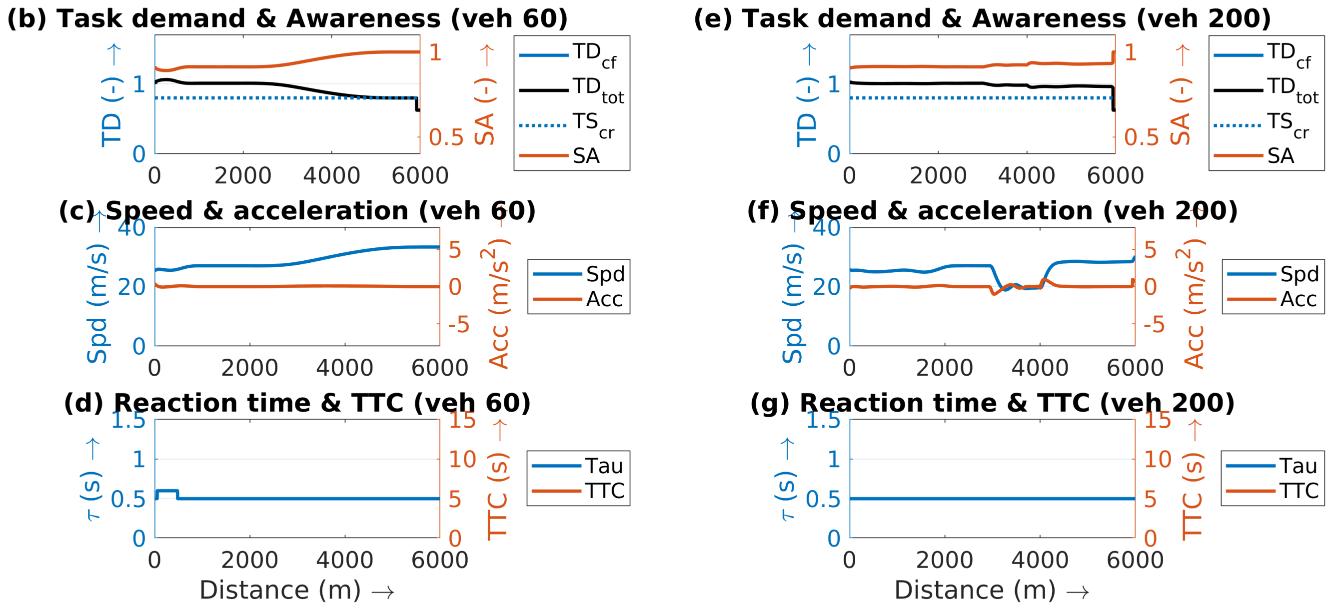
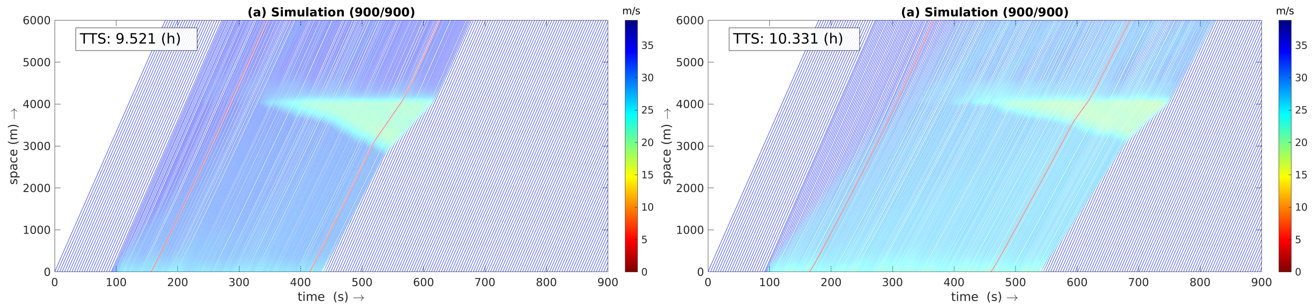


Figure 5.26: Fundamental Diagrams of flow-density and speed-density in case of PEV overestimating the distances

5.2.4 Heterogeneity

In this section, we discuss the heterogeneity as a difference of task capacity of the drivers which reflects their biological and constitutional characteristics. This fact entails that heterogeneity is only related to the cognitive and physiological level of the framework, even though a large stand of literature postulates that the heterogeneity is the difference of observable parameters, such as the rate of acceleration and velocity changes, to name a few. Looking at figure 5.27 we immediately recognise that the inclusion of TC makes the severity of the bottleneck under rainy conditions less predominant. In the case of low rain intensity, the bottleneck severity is lower than the previous simulations when the TC differences were excluded. As a first remark, we can indicate that the effectiveness of some higher-skilled drivers can provide better stability to the traffic stream as their responses are more accurate, which is somehow intuitive to the rudimentary understanding. Other than that, we can discern platoons of different desired speeds, this is something that is seen especially in the case o low-intensity rain. On the contrary, in the case of severe rain intensity, the traffic stream seems to have homogeneity in terms of desired speed. Especially, in this case, the bottleneck starts to fade away and turns into pinned localized traffic. This transformation occurs due to the fact of behavioural adaptation on speeds and time headways. The lower speeds of the vehicles make the congestion slower propagate to the upstream, this is easily derived if one makes use of the shock-wave theory to measure the so-called wave speed, while the larger time distances make the interactions of the vehicles disappear. Lastly, another noteworthy observation here is pointed out in the case of high-intensity rain. We observe that right after the front of the bottleneck, variations with regards to the speeds of the vehicles are made easier for those drivers with relatively high TC than those with low TC. In other words, the relaxation to the desired speed for the first drivers is smaller than the second "category" of drivers. This allegation is supported when plotting the hysteric patterns in figure C.4.



(a) Rainy conditions (1.0mm/h)

(b) Rainy conditions (10.0mm/h)

Figure 5.27: Emergent patterns

All in all, the last scenario which combines all the psycho-cognitive and kinematics mechanisms and the concept

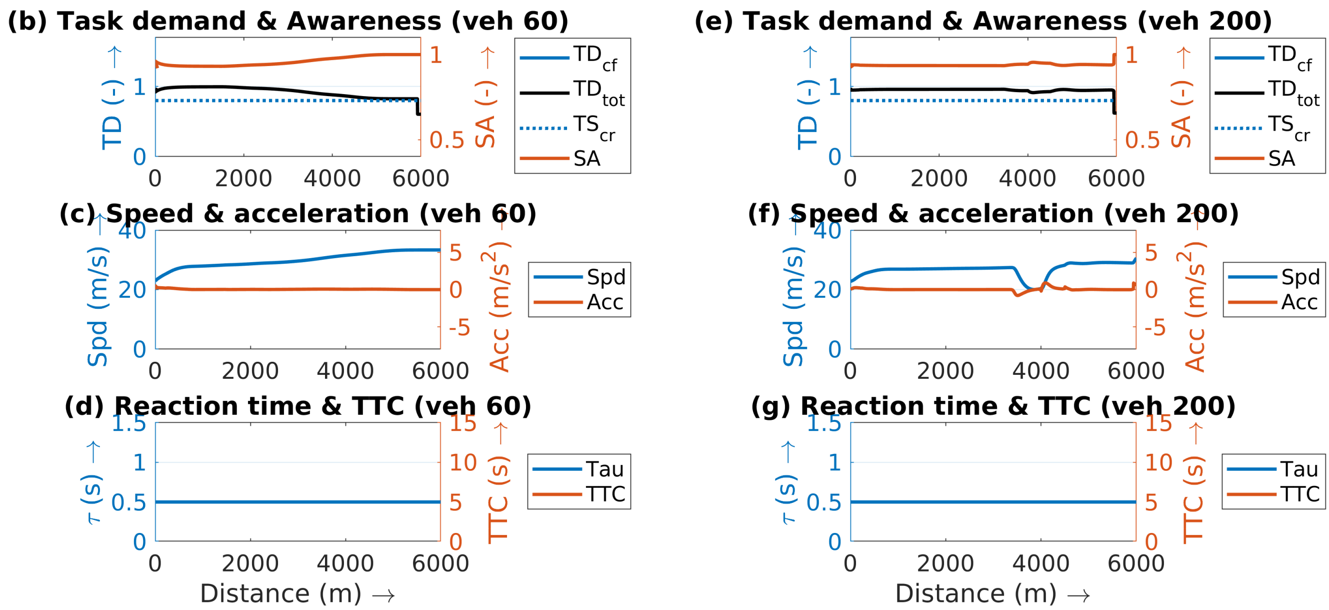


Figure 5.28: Fundamental Diagrams of flow-density and speed-density in case of PEV overestimating the distances

of heterogeneity is very promising from the following aspects. The first is from the aspect of efficiency as the mean speed is within the acceptable boundaries according to the literature review in Chapter 2. In terms of safety, we can argue that the traffic stream has not any particular problem to traverse the segment as the indicator of TTC is very high (in terms of seconds). This surrogate safety measure reveals that safety is guaranteed for the present case. For all these reasons we attempt cross-validation with an empirical study conducted by (Chung et al., 2006) on highways of Japan. The indicator that we use here is the speed and regards the macroscopic level. In the empirical study, as we illustrate in figure 5.29 the reduction of speed starts from 4.5% for rain intensities 0-1 mm/h, continuous with 4.6% for 1-2 mm/h, 5.6% for 2-3 mm/h, 6.4% for 3-4 mm/h and results in 8.2% for 5-10 mm/h. At the same figure, we see the development of speed reduction from the output of the last scenario. We start with rain intensities of 0-1 mm/h and reduction 2.2%, we continue with 2.7% for 1-2 mm/h, 2.7% for 2-3 mm/h, 3.9% for 3-4 mm/h and results in 7.9% for 5-10 mm/h. The first observation is that the speed reductions for the simulation case is lying between the acceptable boundaries that the empirical observations reveal. The amplitude of the reductions is competent with the one of empirical observations and with no doubt, they do not match exactly. Regarding the trend of the reductions, we can point out that generally, the speeds have the propensity to worst off as the intensity of the rainfall increases. Respectively, we see that for the first three bins the speed reductions have approximately the same amplitude. This is evident by looking at each case,

i (mm/h)	TTS(h)	Collisions	u(km/h)	k(veh/km)	q(veh/h)
0	9.316	0	112.45	12.89	1451
0.5	9.448	0	110.88	13.08	1451
1.0	9.521	0	110.04	13.18	1451
2.0	9.570	0	109.47	13.25	1451
3.0	9.536	0	109.86	13.20	1451
4.0	9.684	0	108.18	13.40	1451
5.0	9.726	0	107.71	13.46	1451
6.0	9.843	0	106.44	13.62	1451
7.0	10.086	0	103.87	13.96	1451
8.0	10.081	0	103.92	13.95	1451
9.0	10.236	0	102.35	14.17	1451
10.0	10.330	0	101.35	14.30	1450

empirical and simulation, respectively. On the contrary, the speeds are impacted considerably when the rain intensity is between 5-10 mm/h. Therefore, the following can be put forward:

- The psycho-cognitive mechanisms with the combination of kinematics mechanisms have the potential to explain and generate aggregate behaviour competent with the one we admit in observations.
- Even though a large number of assumptions regarding the parameters' values, and how the psycho-cognitive mechanisms influence each other and the response of the vehicle kinematics, we obtain a plausible response of the model.

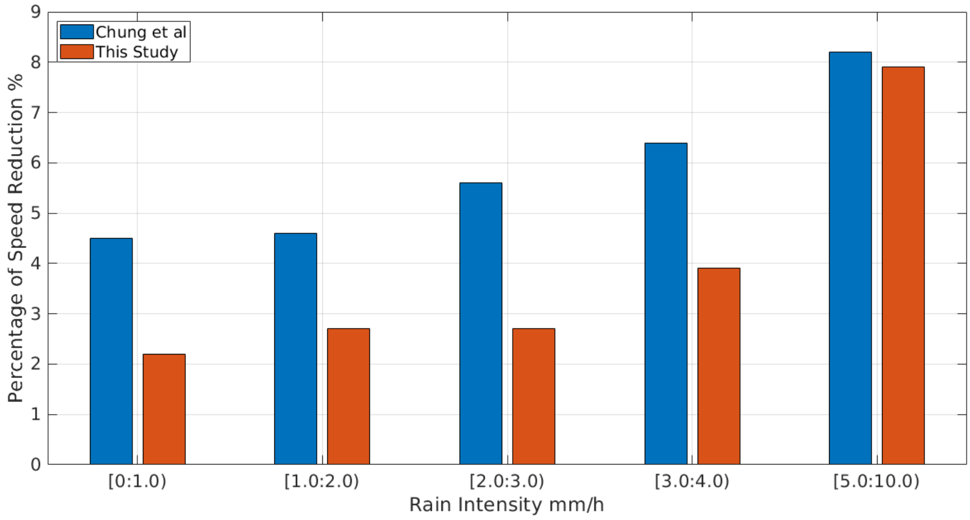


Figure 5.29: Cross-validation between the results of this study and the study of (Chung et al., 2006) that was conducted in highways of Japan

5.3 SIMULATING FOGGY CONDITIONS

We will simulate three distinct foggy conditions; clear visibility conditions, moderate visibility conditions and low visibility conditions. In the first set of cases, the visibility distance is 439m, whereas in the second and third case the visibility is 93m and 41m respectively. To translate the visibility conditions into task demand of car following we assume a direct influence of visibility to the time headways. It is hypothesized for the first scenario that the drivers will not suffer from high cognitive load and thus to the whole set of scenarios will perform the same. For the second and the third scenario, we expect that the cognitive mechanisms will exert some impact on the individual and aggregate behaviour yielding the road segment to reach sub-performance. Following the same pattern as we did in the case of rain, we partition the framework and evaluate one at a time the impact of each cognitive mechanism. The results will be concentrated to the cases in which the moderate and the low visibility conditions are in place.

5.3.1 Induced Task Demand

Derived from the literature and the practice, fog affects the visual acuity and the cognitive workload of the drivers. Thus, the first mechanism we allow at the framework is the induced task demand which increases the demand of the task of car following. Among the many studies we have reviewed in this thesis, we choose to exploit the one provided by (Broughton et al., 2007) in which work we distinguish three visibility conditions named clear, moderate and dense.

As we can see in figure 5.30 we discern two distinct patterns, for the population with a mean speed of 22.6 m/s and 13.4 m/s. It is evident that the slow speeders do not affect by the changes invisibility. On the contrary, the high speeders, are affected substantially by the change in their visibility conditions with an effect on the time headway. Once more, we exploit the time headways as a performance measure in order to implicitly derive the cognitive load of the drivers as **??** postulates. In the same figure, we see that the visibility conditions of 93[m] is named **Fog 1** with a mean time headway **8.5 [s]** and the visibility conditions of 41 [m] is called as **Fog 2** with a staggering 8.9 [s] mean-time headway. Under clear visibility conditions, the mean time headway of the vehicles is 2.5 [s]. Having that said, we can derive that the induced task difficulty by the reduced visibility under the two cases is 8.5 [s] / 2.5 [s] = 3.4 and 8.9 [s] / 2.5 [s] = 4.05 more than the initial case of clear conditions. With this knowledge we can perform the first set of simulations which concerns the induced task demand and its effects on **reaction time**. The emergent patterns can be seen in figure 5.34 for the moderate and dense fog conditions.

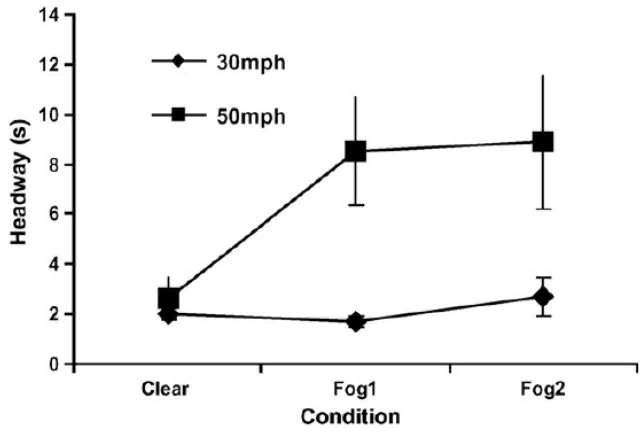
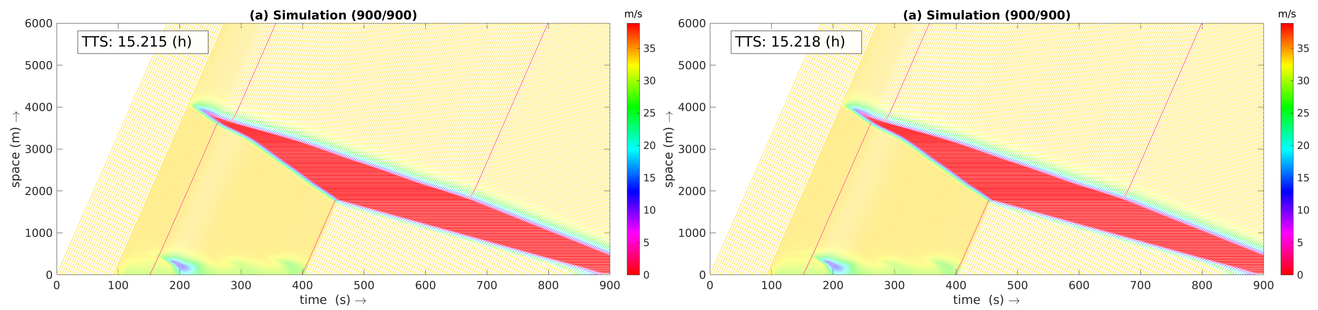


Figure 5.30: Time headway for the whole driving population as derived in the study of (Broughton et al., 2007)



(a) Moderate Fog

(b) Dense Fog

Figure 5.31: Emergent patterns

For both foggy conditions the performance of the road segment is competent, even though the patterns are not realistic. These patterns reflect a behaviour of vehicles to be very sluggish and highly irresponsive to the "perfect" stimuli from the environment. The increased reaction time explains the inability of the individuals to react on the stimuli. A better understanding is formed when we look at figure 5.32. We follow two cars with id 60 and 200. For the car with id 60 we interestingly see that the TTC is substantially low and even in which case, there is no incident occured. This fact makes us to conclusively derive that the TTC indicator is an ill-defined indicator of safety. Apart from the obvious results of the TD and SA, no other comment can be done in this case.

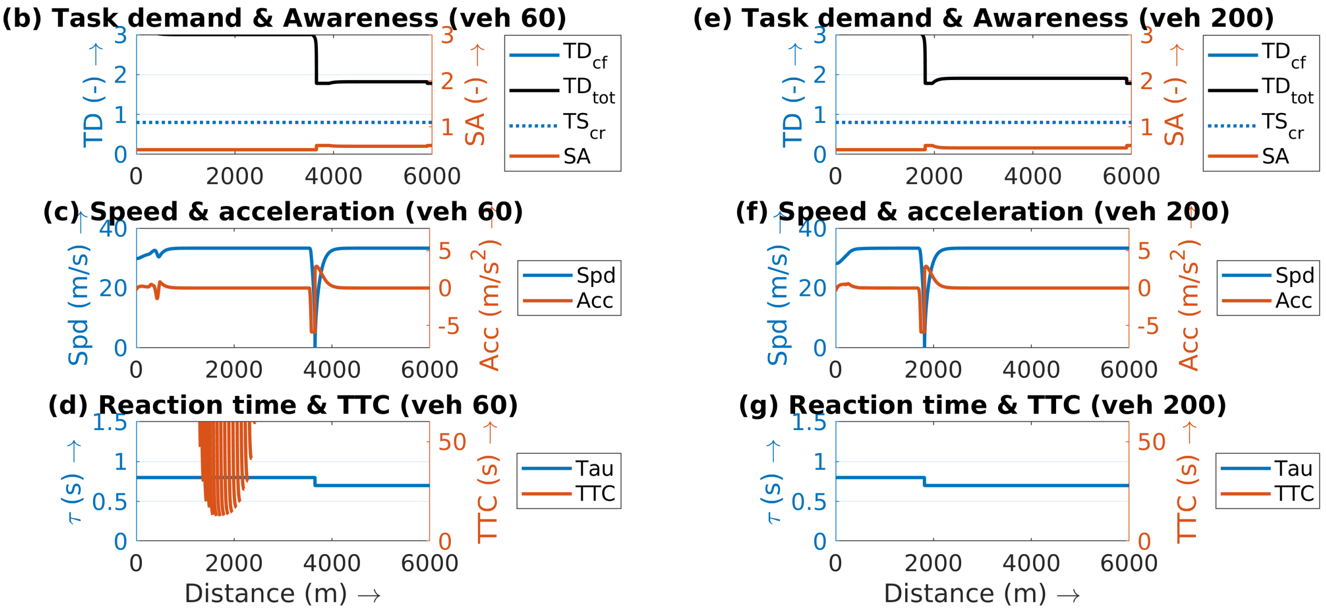


Figure 5.32: Human Factors for the case of dense foggy conditions

Regarding the correctness of the underlying theory of traffic flow, we plot at figure 5.33 the fundamental diagrams. It is evident from the fundamental diagrams that the theory holds good as the anticipated scatter-plots

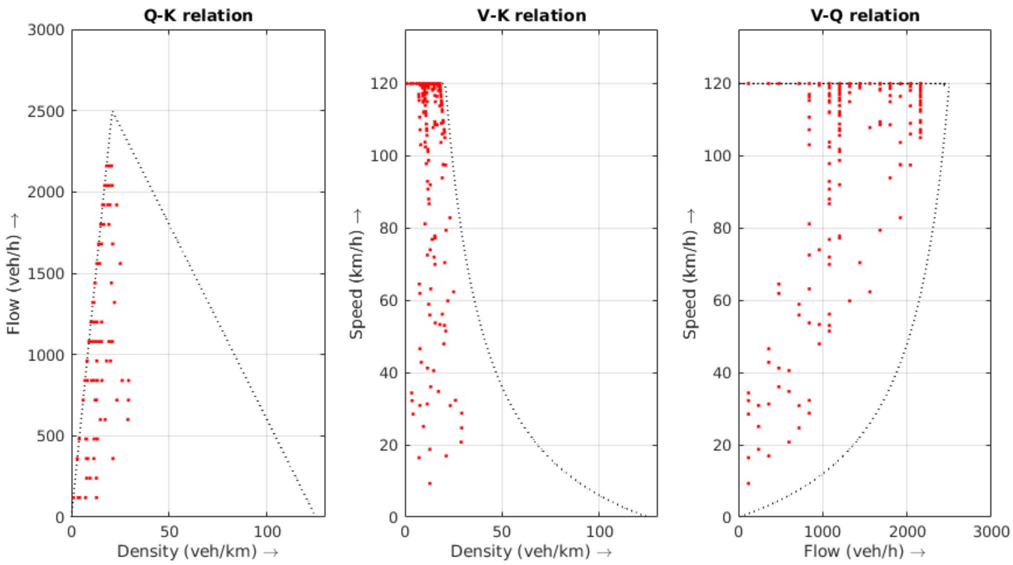
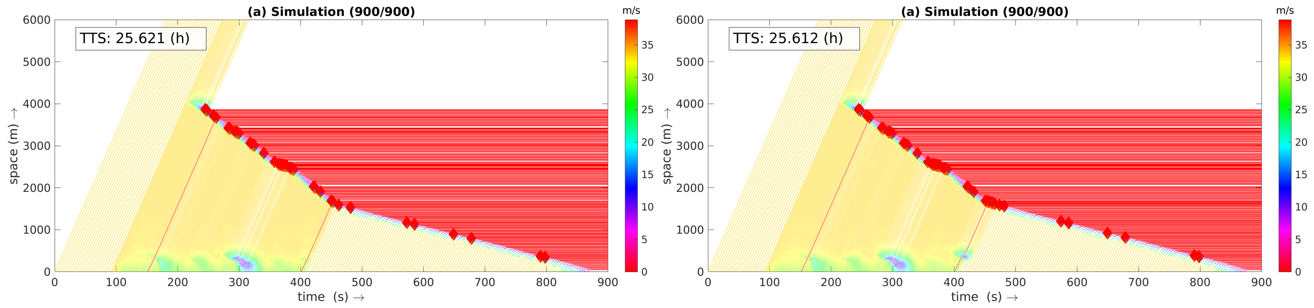


Figure 5.33: Fundamental Diagrams of flow-density and speed-density in case of RT

shown in the figures. In figure 5.33 we plot the **Q-K**, **V-K** and **V-Q** relationships. The uncongested branch is seen in the first figure while the scatter indicates the traffic stream fluctuations.

5.3.2 Perception Errors on Speed

In addition to the previous set of simulation we include the perception errors on speed differences as an additional effect. We assume that the vast majority of the driving population overestimate the stimuli, this means the 75% and we give some room to 25% of the driving population to underestimate the stimuli. Remarkably, the traffic stream results to incidents for the both foggy conditions. For the moderate foggy conditions the number of collisions is 39 while for the dense foggy conditions is 43.



(a) Moderate Fog (b) Dense Fog

Figure 5.34: Emergent patterns

These rear end collisions occured from the combination of the increased reaction time and the inefficiency of the drivers to estimate the ground truth speed differences. Looking at the equation 5.3.2 we immediately see that the influenced parameter of speed differences is in the numerator and with the combination of the rest parameters gives larger value of acceleration/deceleration values.

$$1-\left(\frac{s_0+u_n*T+\frac{u_n*(1+\delta*\epsilon_i^{SA})*\Delta u_i}{\sqrt{a_{max}*b_{comf}}}}{(1+\delta*\epsilon_i^{SA})*s_i}\right)^2 \tag{5.2}$$

As an example, we look at the human factors for the case of moderate foggy conditions. Both selected drivers

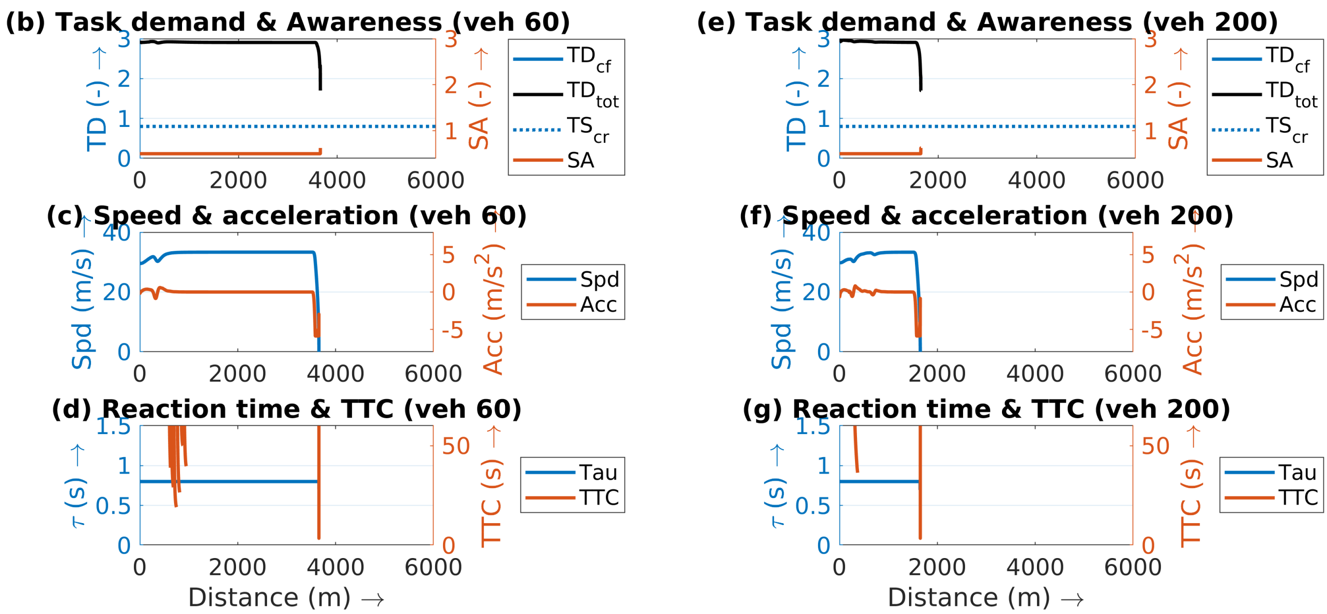
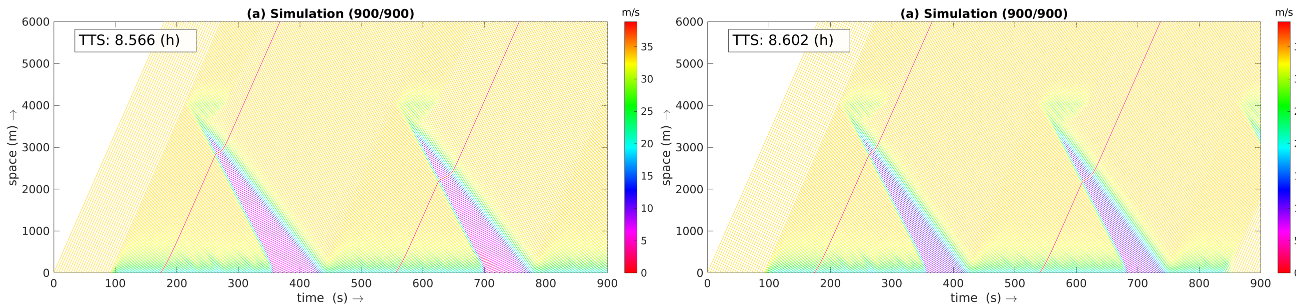


Figure 5.35: Human Factors for the case of moderate foggy conditions

suffer from high TD and low SA and this yields to relatively high reaction time and large, always proportional to the low SA, perception errors of speed differences. From the perspective of safety, the TTC indicator gives the correct implication when its value is low. Rear end collisions occured for very low TTC values.

5.3.3 Perception Errors on Distance

In this subsection, we combine the additional effect of the misconceived distance stimuli. From the literature review, we know that the vast majority of the drivers overestimate the distances and especially there are empirical relationships that describe this relationship. The one that we use was addressed and analysed in Chapter 3 and it is in a power-law form (equation 3.34). By this knowledge, we assume that the additional cognitive load of the TD will exacerbate this estimation of distances towards a bias governed by the power-law form.



(a) Moderate Fog

(b) Dense Fog

Figure 5.36: Emergent patterns

Interestingly, we observe that no collisions occur for the both foggy conditions. The emergent patterns depicted in figure 5.36 reveal two distinct wide moving jams propagating to the upstream with a starting location, the location of the bottleneck. These jams as they propagating backwards amplified by the fact that the demand of the vehcilces that want to enter the segment is stable and high. Regarding the human factors dynamics we plot

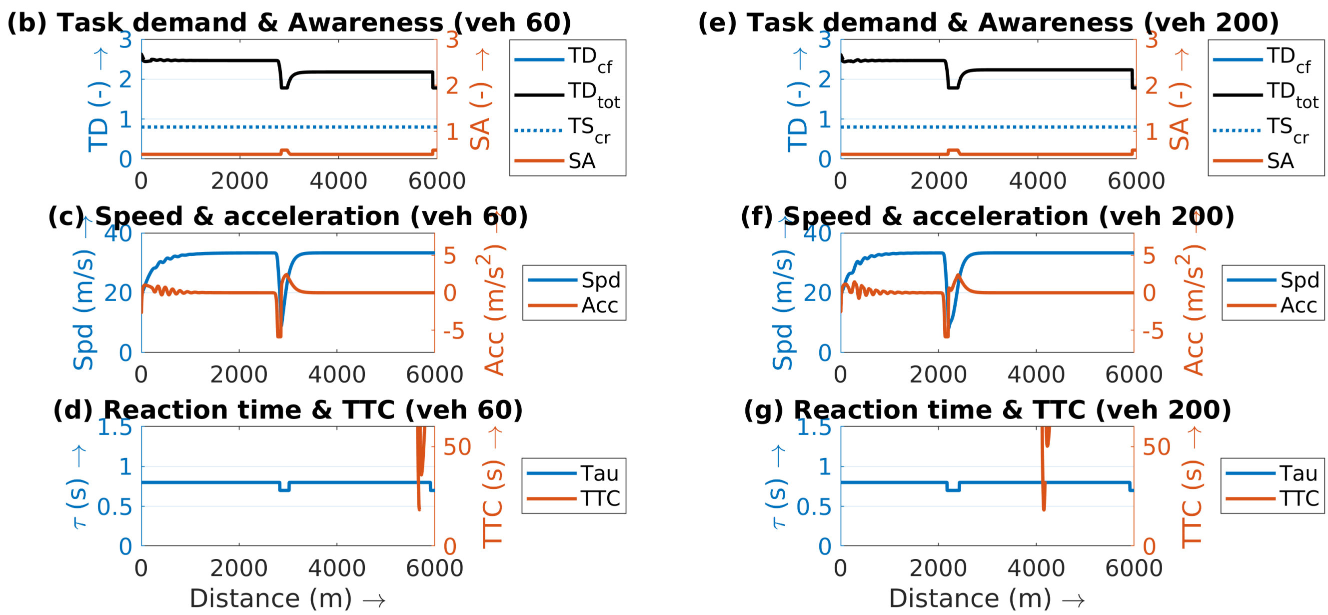
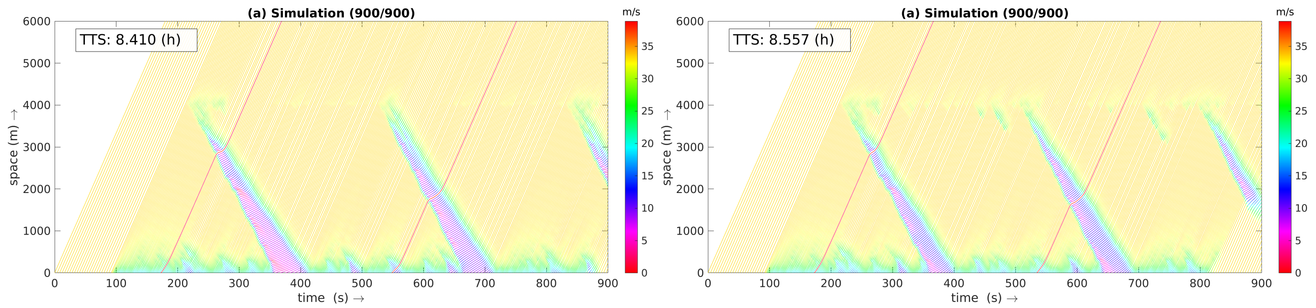


Figure 5.37: Human Factors for the case of dense foggy conditions

the relevant state variables in figure 5.37. The task demand is relatively very high and the SA is low with a result to a degraded perception ability. Besides the start of the simulation, the speed and the acceleration trend remain the same with no many oscillations. For the vehicle 60, even if it suffer from very low SA, reacts correctly to the stimuli when it came across to the first moving jam. This is remarkable here, as with such a low SA we expected the vehicle to end in a collision. After that, regains its speed and continue undisturbed as it gets to the end of the simulation. The same pattern with not any difference observed for the vehicle 200. The interesting fact here is that the drivers with very high reaction time 0.8 [s] they can deal correctly with the task of car-following.

5.3.4 Perception Errors on both stimuli

When we allow both perception errors to the simulation we do not observe any collisions and the performance of the network is nearly competent with the previous case in terms of efficiency (TTS). More specifically the TTS in case of moderate fog is 8.410 [h] and 8.557 [h] far less than the clear conditions case but this is logical. The number of cars of the specified time-space window for the case in the foggy conditions is less than the clear conditions. The spatio-temporal patterns here are two wide moving jams propagating towards upstream and they reach the boundaries of the simulation.



(a) Moderate Fog (b) Dense Fog

Figure 5.38: Emergent patterns

Human factors are depicted in figure 5.39 for the cars 60 and 200 during the dense foggy conditions. Both cars are suffering from very high task demand and experienced low SA. Nevertheless, they still can react to the the stimuli correctly.

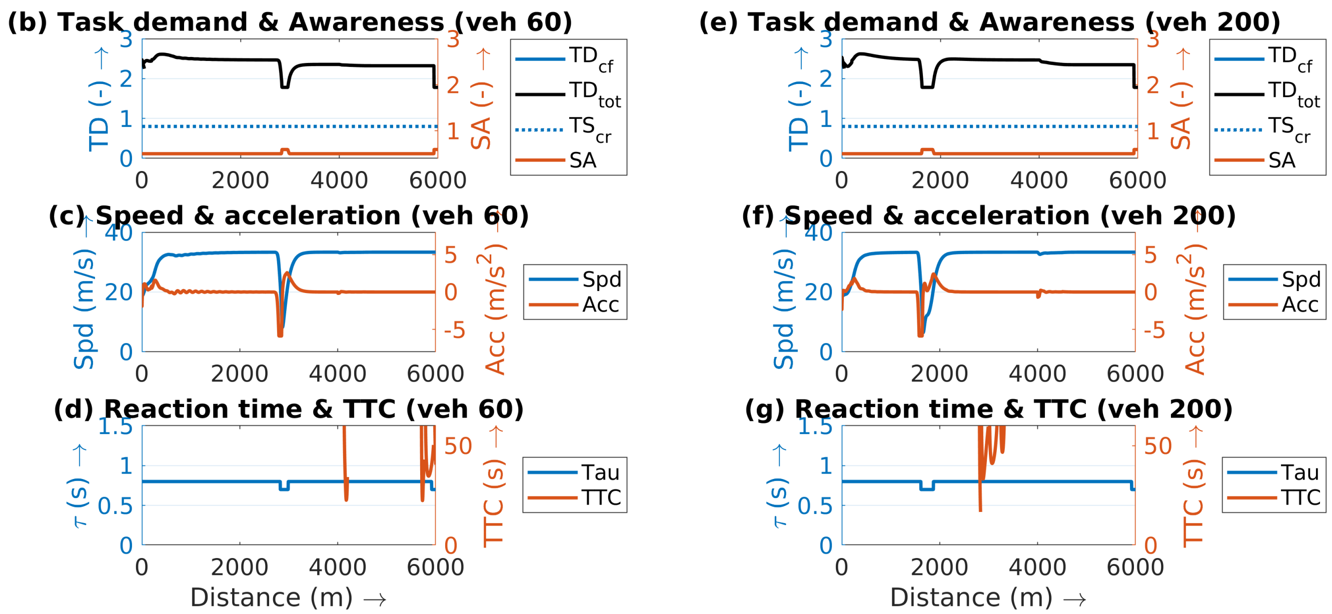


Figure 5.39: Human Factors for the case of dense foggy conditions

Lastly, we investigate the concept of the behavioural adaptation on preferred speed.

5.3.5 Behavioural Adaptation on preferred speed

When we conducted the first simulation of the behavioural adaptation on the speed we discovered that the effect of response on the proffered speed is significantly large yielding unrealistic results on the traffic stream. To expand deeper, the emergent patterns were even out leading to a smooth behaviour of the stream as if VSL is in effect. For this reason, we decided to conduct a sensitivity analysis on the $v0_{fac}$ by running 4 simulations plugging in the values 0.1,0.2,0.3 and, 0.4. This constant can be found in the code implementation of the behavioural adaptation and it is a trick to amplify or de-amplify the effect of the behavioural adaptation. It turns out, that even with the rational assumptions between the perceived risk and correction on the control parameters, some calibration of the parameters needs to be done to achieve plausible behaviour in terms of emergent patterns, state variables and performance of the network. There is no doubt that this mathematical formulation does not reflect any physical quantity of the driver. On the contrary is an effective way to apply the behavioural assumptions. As a reminder we present the following euation that encompasses the assumptions that we have made:

$$v_i^0 = (1 - \beta_i^{v_0} \epsilon_i^{TS}(t)) * v_i^0 \tag{5.3}$$

The $\beta_i^{v_0}$ parameter is the one that governs the strength of the behavioural adaptation. In the case of rain we had set the parameter to the value of 0.9, here in the fog case we first try some values, especially low as as we have already mentioned the results are not representative. The parameter $\epsilon_i^{TS}(t)$ encloses the difference between the defined critical task saturation and the real time task saturation. In other words, drivers are motivated to reduce their speed, in this specific case, as an alleviation mechanism for their high perceived risk. The last parameter of the equation is the initial desired speed. The results of this sensitivity analysis are included in terms of mean speed in figure 5.40.

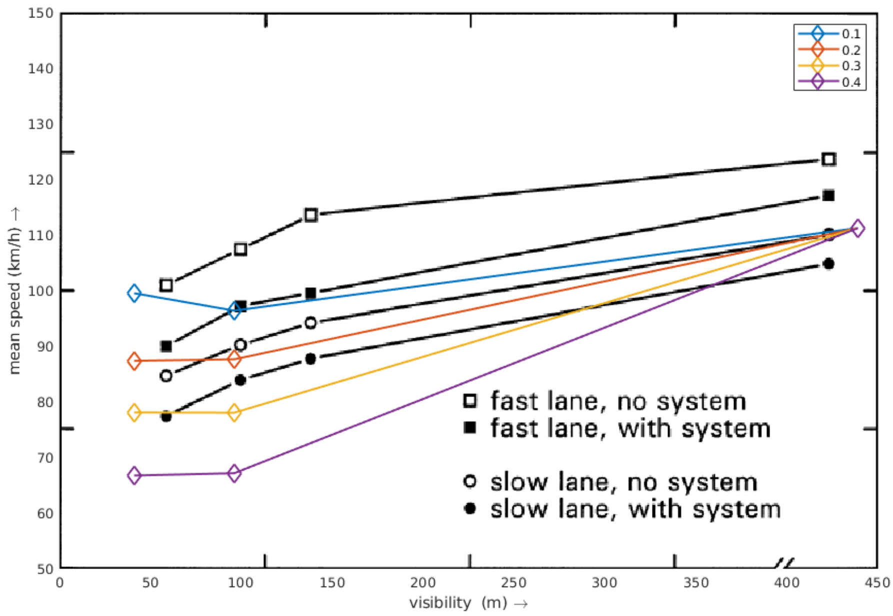
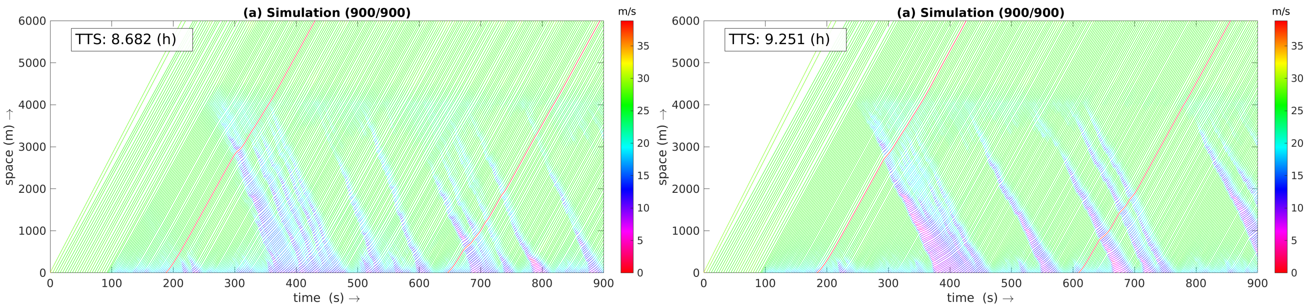


Figure 5.40: Human Factors for the case of dense foggy conditions

As a solid representative example here, we use the empirical study of (Hogema, 1996) which was conducted in the dutch two-way motorway A16 during various visibility conditions. It is not expected that the results produced from this simulation match with the results observed in the field on the motorway, this comparison is performed as a verification strategy for this model. At the same figure, we plot the sensitivity analysis on the $\beta_i^{v_0}$ parameter while superimposed the results of the empirical study of 5.40. In the empirical study, the level of detail is high as it is presented the mean speed for the two lanes of the motorway named fast and slow lane. In addition, information regarding the warning system of VSL is presented. From this specific example, we conclude that the most likely value range of the $\beta_i^{v_0}$ parameter is between 0.1 to 0.3. Considering this fact, we define in the last simulation that the $\beta_i^{v_0}$ parameter will have value of 0.2. The emergent patterns of this simulation is seen in the following C.4 figure.
The above results show that the vehicles generally slow down as it was expected to happen and at the location of the induced bottleneck multiple stop-n-go waves initiated with a propagation direction to the upstream. Out



(a) Moderate Fog (b) Dense Fog

Figure 5.41: Emergent patterns

of any supplementary empirical evidence we cannot argue that this patterns is irrational. Regarding the human factors of the selected vehicles these are plotted in figure 5.42. It is remarkable how the vehicle 200 with almost zero SA can respond to the stimuli of the driving and reach the end of the simulation without occurring any collision. In figure 5.43 are depicted the mean speed and the flow of the road segment for the various visibility

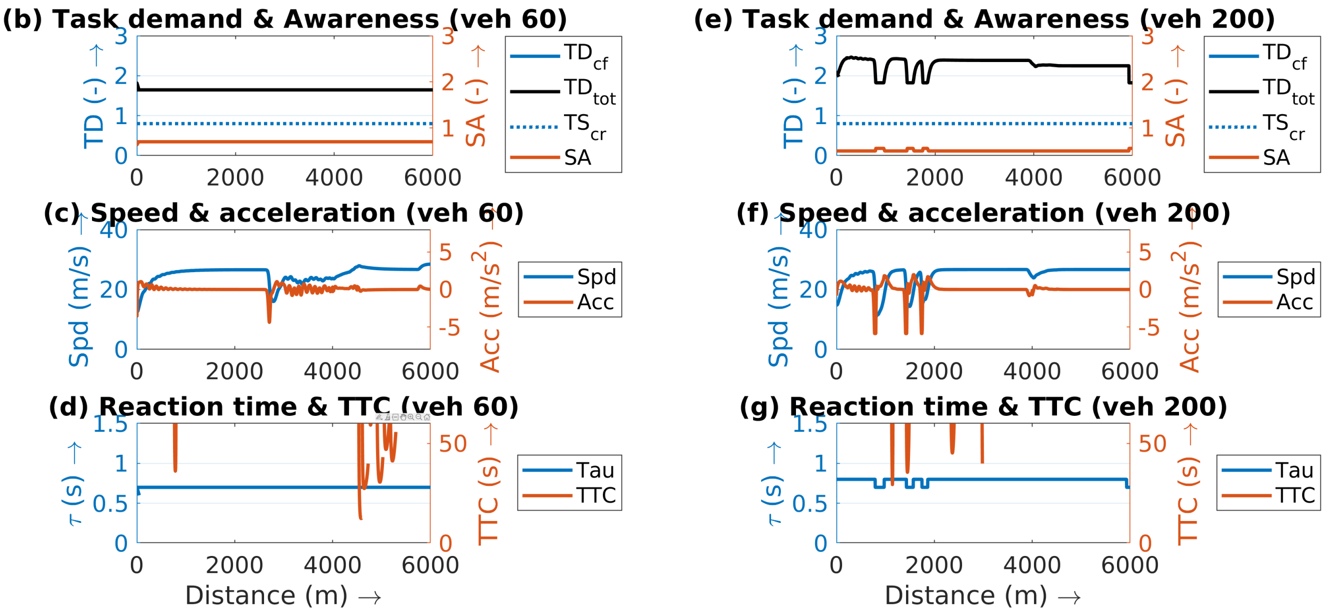
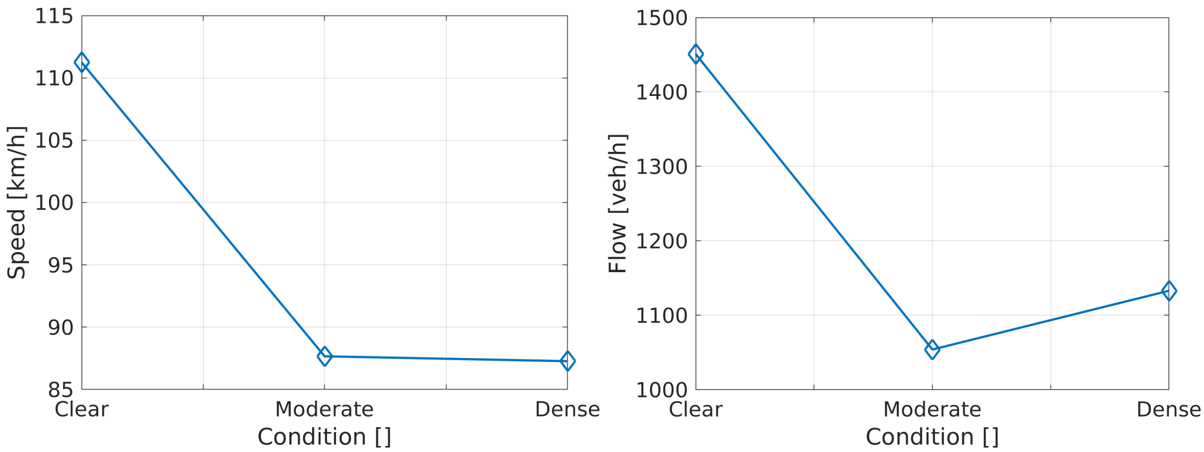


Figure 5.42: Human Factors for the case of dense foggy conditions

conditions. For the moderate foggy conditions the mean speed drops to 87.66 [km/h] and the flow is 1054 [veh/km]. Accordingly, not many changes observed for the dense fog conditions as the drop in mean speed is 87.27 [km/h] and the flow slightly increased to 1133 [veh/h].

5.3.6 Sub-Conclusions

In the present sub-sections, we studied the effects of behavioural mechanisms that initiated in the case of foggy conditions. We partitioned the conceptual framework into smaller parts to assess the performance of the model and the plausibility of the results. We started by considering that the induced task demand will exert some impact on the reaction time. Indeed, we saw that the reaction time has a significant impact on the behaviour of the drivers by making them sluggish to react on time to the stimuli. However, the emergent patterns in figure 5.34 revealed an unrealistic behaviour as the drivers come to a standstill position for a considerable amount of time. Regarding the performance indicator of TTS, we found out that it is the same for both foggy conditions.



(a) Moderate Fog

(b) Dense Fog

Figure 5.43: Speed and Flow degradation for the various visibility conditions

With regards to the capacity of the road segment, we found that 1.196 [veh/h] and 1192 is the capacity for moderate and dense conditions. The mean speed of the segment for moderate and dense fog is 54 and 56 km/h accordingly. From the safety perspective, there are no collisions occurred for both simulations.

Thereafter we conducted experiments by considering perception biases due to the reduced visual acuity of the drivers. From the various studies in the literature review, we concluded that there is a vast majority of the drivers that overestimate the stimuli from the environment. Nevertheless, we arbitrary impose a small proportion of the drivers to suffered from underestimation biases. On top of the reaction time influence, we set, in addition, a degraded perception speed stimuli capabilities. In which case, we surprisingly admit collisions to the traffic stream for both cases of fog. More specifically, we registered 39 and 43 collisions for moderate and dense foggy conditions. Thus, the performance of the segment is degraded to the lowest level in terms of TTS, capacity and speed. It was expected that the speed perception was not a definite parameter for the safety of the network, although our anticipation in the first place was wrong. It is worth mentioning here that in the case of dense foggy conditions the TTS became 25.16 [h], the capacity dropped abruptly to 760 [veh/h] and the mean speed to 21.44 [km/h].

When we only include the biases of the distance estimation which is governed by the power-law form we obtain results with no collisions to the road segment. In this specific case, we assumed that the low SA will exert an impact on the already distorted distance estimation in a proportional manner following the direction of bias that the power-law form equation indicates. The emergent patterns we observed in this case are two wide moving jams starting from the upstream of the bottleneck and propagate backwards with an amplified manner. The first deficit appeared in this case as the speed of the wave stream is propagating with a speed of 144km/h approximately, and thus the theory of traffic flow tells us that is by far out of the observable boundaries. This amplification is due to the high and stable demand patterns of the segment. The TTS is 8.566 and 8.602 [h] for moderate and dense fog conditions.

Interestingly, we continue by implementing both perception biases of speed and distance estimation. The performance of the network is registered to 8.4 and 8.5 [h] for moderate and dense foggy conditions. There are no collisions we can admit to the network. Nevertheless, the propagation of the wave speed again is too high from the acceptable boundaries.

Lastly, in addition to the perceptual mechanism we have analysed above, we apply a risk avoidance mechanism of behavioural adaptation and specifically on speed. By using an empirical study to cross-validate the plausibility of the results we have concluded that the adaptation on the speed is not proportional to the perceived risk. On top of that, we investigated the impact of the heterogeneity in terms of different task capacity of the drivers which encloses the different constitutional and biological characteristics with one single indicator. The efficiency of the network was captured by the TTS which for the moderate conditions is 8.68 [h] ad for dense foggy conditions is 9.25 [h]. The mean speed of the network for both foggy conditions is 87 [km/h] while the capacity yielded to 1054 and 1133 [veh/h] accordingly. Even if we consider all the possible mechanisms to explain such a behaviour, while the performance indicators of speed and capacity are quit rational, the wave speed is very

high to consider that the results are plausible in terms of traffic flow theory.
It is worth highlighting here that even if we apply perceptual mechanisms that indicated by the literature and capture the behaviour of a traffic stream which is competent with empirical findings, the level of detail is not that high to attribute differences between dense and moderate foggy conditions.

- How reasonable are the modelling responses of the framework when incorporating human factors to simulate the case of rain?

  In the previous section, we have investigated the possibility of incorporating human factors as endogenous processes to explain and generate rainy conditions. The final simulation when we allowed both the mathematical modelling of vehicle kinematics and the speculative functions that govern the cognitive state of perception and response seems to yield a feasible and reasonable response of the model. For instance, judging the model for its efficiency, the magnitude of the mean speed of the model is at the same order of magnitude with empirical studies. Regarding the capacity, no safe conclusions can be derived as it remains intact. From the safety perspective no collisions occured in this particular case.

- How reasonable are the modelling responses of the framework when incorporating human factors to simulate the case of fog?

  In the last section of this chapter, we investigated the inclusion of human factors as endogenous processes to explain and generate the performance of the traffic stream during the environmental condition of fog. We conclude that by taking reasonable assumptions the response of the model cannot reproduce the behaviour that is observed in empirical studies in terms of trajectories. The traffic stream shows that the wave speed is too high and far from the acceptable values that we observe. By only considering the performance of the segment in terms of capacity and speed, the values seem reasonable. It is speculated that the visibility function that we included in the framework first, is ill-defined and does not match with our case, or second, it needs further calibration with empirical data. This is pointed out as we observed that the trajectories of the traffic stream change dramatically when we plugged in this mechanism. In the last section when we performed the calibration with respect to the behavioural adaptation mechanism, we did not achieve to alleviate the ill-defined for this case the visibility equation. Nevertheless, we did achieve to calibrate the response of speed and capacity. In retrospect, the framework may offer plausible results in the condition that the visibility equation is rectified.

- Which methods of validation are applicable in this study?

  Predominantly there are to ways of validating the response of the model. The first way is called face-validation that we ask individuals based on their expertise about whether the response of the model yields to reasonable results as well as about the input-output relationships are working as intended to work. The second way is called operational validation wherein plots and KPIs are plotted to check the consistency of the modelling and the assumptions being made. In the case of rain we utilize both methods. With the established KPI's we admit that the framework performs well and according to the underlying theories while the face-validation method used to assess the amplitude of the results.

At this point, we answer to the final research sub-question which is: **what is the performance of the framework?**:

Interestingly, the performance of both conceptual frameworks is capable of generating and producing reasonable results for the case of rainy conditions. For the case of foggy conditions the proposed framework needs further research as the response of the model regarding the traffic flow theory does not hold good. Furthermore, the produced results are in good agreement with empirical observations in the case of rain. The inclusion of human factors in the model gives an explanatory power that otherwise is not been possible to attain.

6 LIMITATIONS

In this contribution, many limitations are related to the assumptions being made for the successful development of the framework. In this chapter, we highlight the most important limitations.

One of the foundations of this framework is the theoretical assumption that postulates the drivers reduce their speed and/or headway to reduce the imbalance between task demand and capacity. This assumption is in line with the work of (Fuller, 2005) theory of allostasis. Empirical analyses for these condition-specific events show that the drivers in the case of rain reduce their speed and increase their headway from their predecessor, while in the case of fog, drivers reduce their speed. For instance, this contradicts against the results that presented in the contribution of (R. Hoogendoorn et al., 2013) , which is a simulator study, but it is in line with the empirical studies such as (Hogema, 1996).Another strong assumption we made concerns the capacity(capabilities) of the drivers to remain constant. This assumption is rather unclear from the research body. In a more general view, the decision variables of desired speed and headway are restricted to the car following model and it is very likely to exist other decision variables that define the driving behaviour.

The concept of the induced task demand is a breakthrough concept and is an interpretation of the literature that postulates that the task of car following per se becomes more difficult under the influence of adverse weather conditions. To the best of our knowledge, there is no empirical evidence so far that indicates such a relationship between the concept of task demand and weather conditions. Only allegations about this relationship exists and can be found in (R. G. Hoogendoorn, 2012) and (Cacciabue & Carsten, 2010) and elsewhere in the literature.

Throughout this study, the task demand concept was extensively used as a pivotal point to account for the task of driving. Subsequently, a mathematical formulation was proposed to prove that exerts impacts on performance. Task demand is defined as the amount of effort of a driver to meet the requirements of a task, independent of the driver. With this definition, we understand that the task demand is an objective measure that is independent of the driver while registers the important parameter of an environment that constitutes a task. To a certain extent, we effectively achieve the goal of the definition given previously, to be objective, however, we made some assumptions that are crucial to discuss here. By and large, we assume that the only parameter of the environment that affects the TD is the time headway. Such a simplification may work in our framework but in reality, there would be many more parameters that a task (demand) is subjected to. This simplification was in the framework's favour as the implementation of the model was applied straightforward. For instance, in the case of foggy conditions, the distance can play a significant role in the task demand as there is a certain point that the visual acuity is lost whereas the detection of objects (cars, pedestrians) is simply impossible. It is statistically confirmed through control experiments the existence of "critical" headways that drivers start feeling risk.

Situation Awareness is a mental construct highly connected with the decision making and the performance of an operator (driver). The assumption that a low SA imposes deterioration to the performance and additionally affects the parameters of speed, gaps and reaction time is guesswork and condition-specific to the framework and mathematical modelling which is proposed. Another remark within the SA is the assumption that we made regarding low SA will deteriorate the already hindered distance estimation due to low visibility. Within this mental construct resides the concept of the projection of the current state into the near future (i.e. anticipation). Anticipation is proven via simulation studies to be a measure that pays off for the stability of the traffic stream in case that the drivers suffer from high reaction times. In this contribution, we did not utilize such a strategy as it would give an additional level of complexity and interpretation of the results.

In this contribution, we assumed that the compensation effects of the drivers regard the control variables of desired speed and time headway. In reality, this might not be true and there are other parameters for immediate control for compensation effects. As an example, we give the maximum behavioural acceleration or deceleration that could work in a model. The author of this study follows Michon's framework and especially the tactical level that in there inhibit the parameters of desired speed and headway. These two parameters are a derivative of planned behaviour, which precedes a well-planned decision-making process, rather than a result of instantaneous and probably subliminal decisions such as the acceleration/deceleration. Generally, the compensating parameters chosen in each study are restricted to the kinematics model having fewer degrees of freedom.

Many functional forms of the underlying cognitive mechanisms are modelled to obey a linear relationship. With the absence of an solid empirical evidence these assumptions that we made are arbitrary at best but give an additional explanatory knowledge to the models.

It is rather unclear, especially in the case of rain, how the perception biases work and what is the favourable magnitude. In addition, it is not yet discovered if the biases to the stimuli pointing towards one direction simultaneously. Under normal traffic conditions, there some evidence towards underestimation of the distances ((Martens et al., 1997),(Nilsson, 2000),(Hiro, 1996)) but for the speed estimation, the direction of the bias is still not known. Influenced by this strand of literature we made a strong assumption that in the case of rainy conditions the biases will follow the pattern of clear conditions giving some room for overestimation.

A general limitation of this study is the model of the car following that we choose to work with. This fact could be a limitation with any other model that we could have chosen to experiment with. A car-following model contains several parameters that may or may not have an intuitive meaning connected with some physical or behavioural properties to the system. Even if IDM+ has intuitive meaning in its parameters, we cannot argue that it is the most appropriate model to yield reasonable results. Many other car-following models can yield competent results and even completely different aggregate behaviour. Hence, depending on the car-following model that someone uses, maybe benefited or restricted.

The full verification of the model, for the time being, is impossible due to the limitations in empirics and how all these behavioural mechanisms act on each other. To expand further, in this contribution we made valid assumptions based on the present empirical evidence, the literature and the common logic to develop such a framework. Even though that the disciplines of cognitive engineering and behavioural psychology give indications and with valid empirical confirmation, more research is needed for developing a complete framework that is valid under all cases.

7 CONCLUSIONS

The main research objective addressed in this contribution is the generation and explanation of the driving behaviour under weather conditions via simulation. After an extensive literature review on the impacts of these two phenomena, we derive that the use of an agent-based modelling approach combining psychological mental constructs is the most appropriate pathway. The derived conceptual frameworks have been implemented in the MatLab environment for further investigation. The original conceptual framework has been developed to the seminal work of (Van Lint & Calvert, 2018) and further developed and modified for the needs of this study. In the ensuing text, we first answer the main research question and then some of the main research findings are highlighted.

What are effects of the adverse weather conditions on the system vehicle and human drivers when executing the tasks of car-following, and how well can mental constructs represent this behaviour when embedded in the core of a simulation logic?

The effects of adverse weather conditions on the system driver-vehicle-road when executing the car-following task are condition-specific. In this study, we investigated the weather conditions of rain and fog separately. Rain influences the system in the following way. Reduces the manoeuvrability of the vehicle due to the less friction on one hand, and influences the cognitive state of the drivers by inducing higher task demand than driving under normal conditions, on the other hand. This higher task demand/ saturation affects the human driver by making them perform errors on the perceived stimuli (speed and distances) and suffering prolonged reaction times. Additionally, drivers to reduce their high perceived risk initiate a decision making logic to influence, at a tactical level, the variables of desired speed and time headway. This logic is called behavioural adaptation. Fog is hypothesized to exert an impact on the cognitive state of the drivers as well. Moreover, fog distorts the information via the visual channel in a predefined manner. Therefore, the perception of the drivers is influenced by making them perform additional errors to the stimuli while having larger reaction times. The behavioural adaptation in the case of fog is the change of desired speed.
In the case of rain, the mental constructs and the additional hypotheses we made, seems to offer a good explanation while the performance of simulations is reasonable, between the acceptable values and face-validated with real observations. However, in the case of fog, the explanation is more challenging. This is yielded by the results of simulations as some of them do not agree with the underlying theory of traffic flow.

This research endeavours to bridge the gap between collision-free car-following model(s) and human behaviour by exploiting cognitive mental constructs at the circumstance-specific cases of rain and fog. These two weather phenomena can cause traffic breakdown and potentially lead to a collision. However, they differ significantly on the impact to the vehicle per se and the driver. In the event of rain, we dissect the impacts to those that affect the vehicle kinematics and those that influence human behaviour and decisions. To account as simple as possible for the impacts of rain on the agility of the vehicle we introduce parameters that address the forces exerted on the vehicle as a point mass. From these forces, the aerodynamic force R_a and the force due to a grade R_g are neglected. The tractive effort and the maximum tractive effort are taken into account in the formulation. The maximum acceleration in the original formulation of IDM+ was substituted by a minimization hybrid term which combines the mechanical and the preferred maximum acceleration of the driver. We restrict the minimum deceleration of the vehicle with a lower limit provided by the equation of $bmax$. This equation includes additional parameters such as the friction coefficient and the efficiency of the brake and the rain intensified. The advantage of this equation is the potential calibration in the light of available data. The second impact is speculated from the literature. The concept of the induced task demand as an additional cognitive load on the task of car following we utilize to account for the degraded visibility of the drivers. This concept is indicated in the literature of (R. G. Hoogendoorn, 2012) and (Cacciabue & Carsten, 2010) and has a solid foundation of the related work of Fuller (Fuller, 2005). The concept of task demand and capability (capacity in our case) are translated from the abstraction of the original work into parameters which plugged in to a further framework of analysis. Such a parameters, due to the inability to be observed in the nature, we set them to take fuzzy and continuous values 0-1.

Continuing on the case of fog, we demonstrated that the results we presented in the corresponding chapter seems to face valid results as the comparison against empirical findings obtained from the literature conveys similar magnitude (macroscopic) performance. By no means were we expected to attain results that would match any literature or even empirical study with a high degree of accuracy. Although that we are able to obtain reasonable results in terms of speed and capacity reduction, the FD show that the wave speeds which are initiated from the location of the bottleneck have very large speeds.

The emergent patterns that we obtained after the simulations are differing for the investigated cases of fog and rain. For the rainy conditions, and have in effect all the possible cognitive mechanisms, with the speculative biases and the kinematics degradation, we observe that the induced, small in magnitude, perturbation is sustained. The generated wave speeds are in line with observations that indicate a mean speed of 18-22 km/h. Remarkable results for the aggregate behaviour we obtained in the case of foggy conditions. Before we set all the cognitive mechanisms, we observed that the perception of speed can cause collisions to the traffic stream, rather than the distance perception as happened in the case of rain. Instead, in the case of fog, we observe that the induced bottleneck creates stop and go waves in the traffic stream. However these produced stop and go waves have very high speed. This emergent behaviour was not expected in advance. When investigating deeper the results we arrive to a conclusion that the wave speed of the generated stop and go waves is far from realistic.

A quite remarkable effect we observed when we allowed the mechanism of behavioural adaptation in the case of fog. Due to the high Task Demand that fog imposes on the car-following task, the drivers' response to the perceived risk was analogous (as we assumed it to be). For this reason, the drivers slowed down to such an extent that the performance of the simulated network unperformed against any empirical evidence. Even if we calibrate this unrealistic behaviour of the traffic stream we can obtain reasonable results with respect to speed reduction and capacity. Nevertheless, the generated wave speeds are not in line with the underlying traffic flow theory as the waves' speed is too high from pragmatic values.

8 RECOMMENDATIONS AND OUTLOOK

In this final chapter we amassed the most important points for further research and development as derived from this contribution.

- Rigorous validation, step by step, about the assumptions accounted for the influence between the psychological constructs. The main psychological constructs that we used in this study is the SA and TCI. For TCI there is some evidence about its functionality whereas the operalization of SA still is speculative.
- During rain events there is the phenomenon of the generated spray from the cars which is an indirect effect. This effect, depending on the demand of the system may cause a significant impact on the already degraded visibility of the drivers and it needs to be taken into account. This effect does not only holds for the car-following task, but also affects the lane-changing behaviour.
- The nature of the simulation is deterministic, as not many stochastic processes are included in the model. A potential extension of this is to include more stochasticity in various processes of the model, such as vehicle generation, attach to the desired speed, noise on acceleration to name a few.
- Visual channel is of paramount importance in driving. When we sensing the stimuli of distance in driving, which is proven to be a prominent parameter is driving, it is good to connect the theory of visibility with the external environmental conditions. In so far, there are some theories scattered in the literature, but more concise and coherent work needs to be done. Admittedly, when we tried to include the some empirical evidence in the framework, the results are not realistic regarding the produced shock-waves' speed.
- Expanding further from the scope of this thesis and considering automated vehicles, this framework can benefit the research by quantifying ground truths of weather conditions between manual driving vehicles and automated vehicles.
- This research was focused exclusively on modelling the car-following task in combination with mental constructs. The next step that goes beyond question is to consider the task of lane changing as the "second fundamental" task in driving. Over the course of the year, many researchers have developed lane-changing models with rule-based criteria, discrete choice models, artificial intelligence, and incentive-based criteria. From all these, the last category looks promising, as it is easier to be calibrated.
- A good benefit in the formulation proposed regarding the vehicle kinematics is the potential coupling with fuel consumption models to investigate and assess the environmental carbon footprint of individual cars of the whole traffic under such events that the fluctuations of acceleration and subsequently speed is more frequent making the vehicles' engine to consume and emit more fuel.
- Cars with augmented perception, planning and control seem to proliferate on the roads promising better individual and aggregate performance. It would be a nice investigation to assess the performance in disaggregate and aggregate scope benefited by such frameworks.

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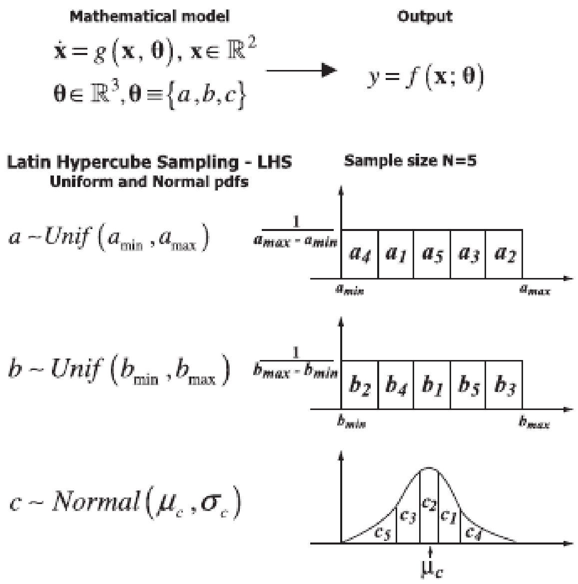
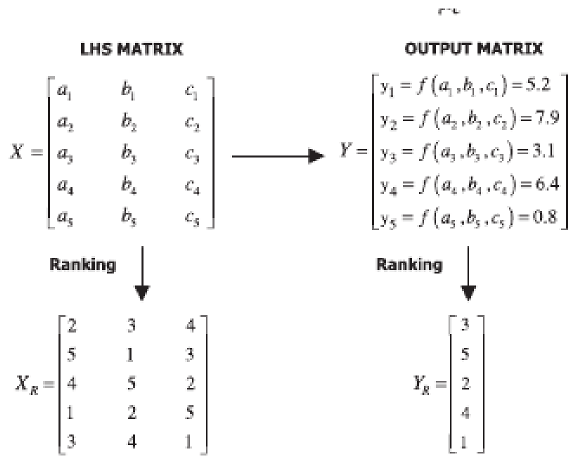
A GLOBAL SENSITIVITY ANALYSIS WITH LATIN HYPERCUBE SAMPLING

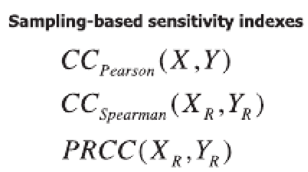
Latin Hypercube Sampling belongs to the Monte Carlo simulation family, performing model simulations using a pseudo-random number sampling for the input parameters set, following a predefined distribution. Each input parameter is sampled over its defined value space using a certain probability distribution function. Should there is no knowledge for the input parameters, a uniform distribution is opted for. The following figure sheds light the steps that one should follow to execute the technique.



(a) Mathematical Model and stratified distributions of the parameters used



(b) LHS matrix and the output matrix of each parameters used



(c) Correlation Coefficient as a Performace Indicator

Figure A.1: General scheme of the LHS technique, (Marino et al., 2008)

The edge of the LHS is that permits of an unbiased estimate of the average model output and at the same time, the requirements of sampling size over the input parameters is smaller than the original MC sampling technique. The accuracy of the model response when using LHS is competent as the MC techniques.

Initially, the input parameters are chosen. Depending on the knowledge and the correlation of the input parameters, if there is ay, distributions are set of each parameter. Each probability distribution function of the

parameters is partitioned into equal intervals and then sampled for values independently. Each interval of each parameter is sampled one time strictly without replacement. With this process, the value space over the input parameters is explored at the greatest extent. The derivative of this technique is the creation of a matrix, which is usually referred as LHS matrix. This matrix constitutes the input of each simulation. Thereafter, the response of the model is further analysed with the use of the sensitivity indexes.
A well used measure of linear association between an input and an output of a model is the Coefficient Correlation(CC). The CC is calculated by the following equation:

$$r_{x,y} = \frac{Cov(x,y)}{\sqrt{Var(x) * Var(y)}} = \frac{\sum_{i=1}^{N}(x_{ij} - \bar{x}) * (y_j - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_{ij} - \bar{x})^2 * \sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{A.1}$$

In the case that the correlation between the parameters is not linear, the partial correlation (PCC) is consulted as a statistical measure between input and response whereas the influence of the rest input parameters is discounted. The PCC between x_j and y is calculated as the CC between the residuals of (x_j - $\bar{x}_j$) and (y_j - $\bar{y}$). The $\bar{x}$ and $\bar{y}$ are following linear regression models as shown below:

$$x_j = c_0 + \sum_{p=1,p<>j}^{k} c_p x_p \tag{A.2}$$

and

$$\bar{y} = b_0 + \sum_{p=1,p<>j} b_p x_p \tag{A.3}$$

If the data are rank transformed, then the partial rank correlation coefficient is calculated. The PRCC is a robust sensitivity measure for non-linear but monotonic relationships as long as the input data have little correlation.

B PARAMETERS FOR INCLUDING VEHICLE CHARACTERISTICS

In the following table are the parameters that have been used in the simulations. The first column is the symbol used in the equations and the implementation in MatLab, the second column is the value derived from the literature (fourth column), and at the last column is given an explanation.

Table B.1: Parameters used for face validate the mathematical formulation of the vehicle model kinematics for car following

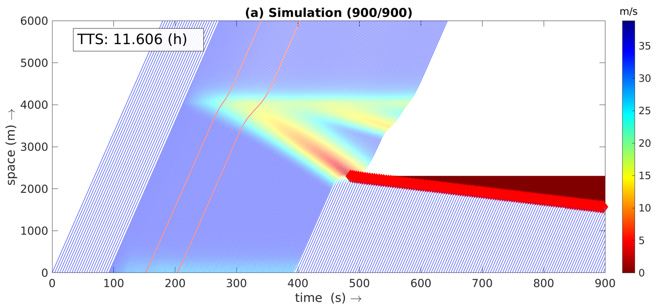
Parameter	Value	Units	Literature	Comments
m	1400	[kg]	(Rakha et al., 2012)	Mass of the vehicle
m_{ta}	-	[kg]	(Rakha et al., 2012)	Vehicles mass on tractive axle
$perc_{mta}$	[0.50-0.62]	[%]	(Rakha et al., 2001)	Percentage of mass on tractive axle
μ	[0.4-0.65]	[-]		Friction coefficient
C_r	1.25	[-]	(Rakha et al., 2001)	Rolling Resistance coefficient for road surface
c2	0.0438	[-]	(Rakha et al., 2012), (Rakha et al., 2001)	Rolling resistance coefficient for road condition
η_b	0.85	[-]	(Mannering & Washburn, 2020)	Braking efficiency
η	0.89	[-]	(Mannering & Washburn, 2020)	Transmission efficiency
ri	[0,1]	[cm/h]	(Rakha et al., 2012)	Rain intensity
a_{max}	$f(..)$	$[m/s^2]$	(Rakha et al., 2001),(Rakha et al., 2004)	Maximum acceleration
b_{max}	$g(..)$	$[m/s^2]$	(Rakha et al., 2012)	Minimum acceleration
P	90	[kW]	(Toyota, 2021)	Engine Power

Table B.2: IDM+ parameters

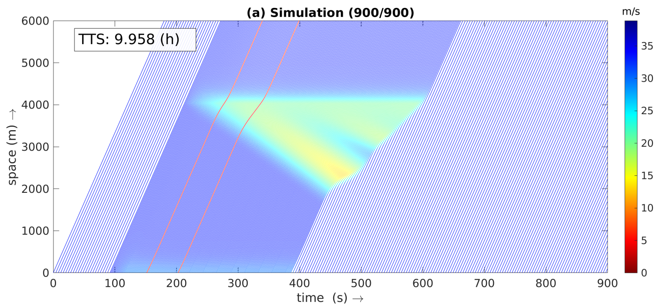
IDM+ PARAMETERS			
NOTATION	***VALUE***	***UNITS***	***DESCRIPTION***
τ	0.5	seconds	Reaction Time
amax	3	m/s2	Maximum Acceleration
vo	33.33	m/s	Desired Speed
so	8	m	Stopping Distance
T	1.2	seconds	Minimum time headway
bcomf	2	m/s2	Comfortable deceleration
delta	4	$\sim$	Aggresiveness
bmax	8	m/s2	Maximum Deceleration

C EMERGENT PATTERNS BASE CASE CALIBRATION

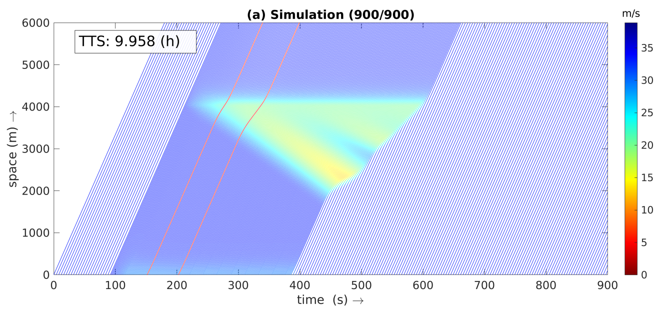
This chapter regards the calibration of the model with respect to the base case.



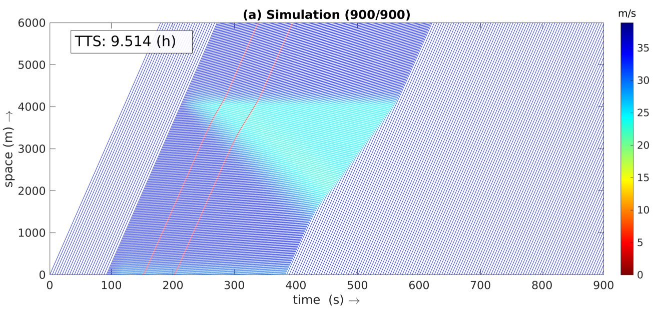
(a)



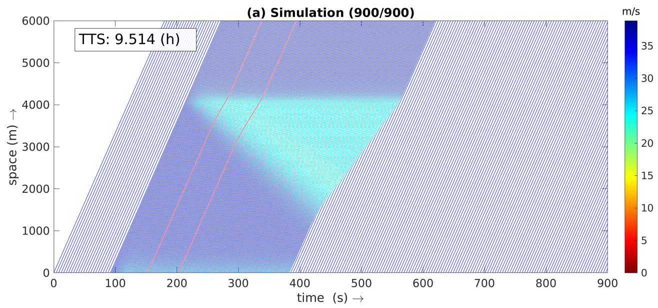
(b)



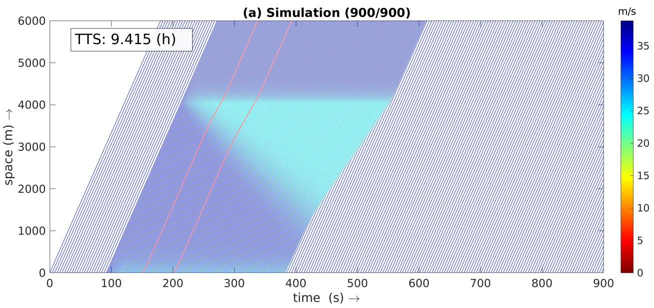
(c)



(d)



(e)



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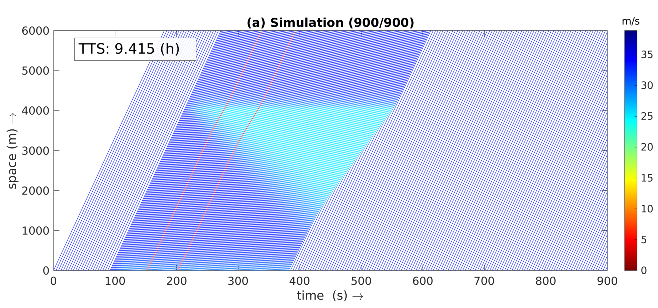
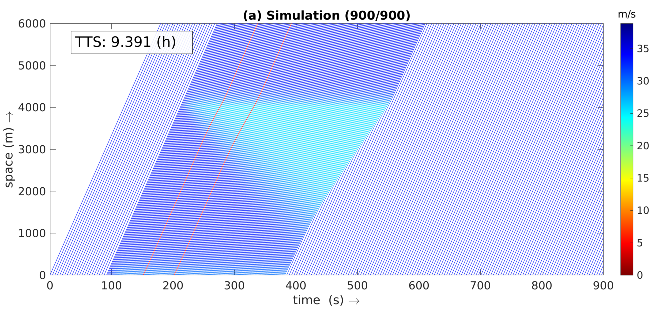
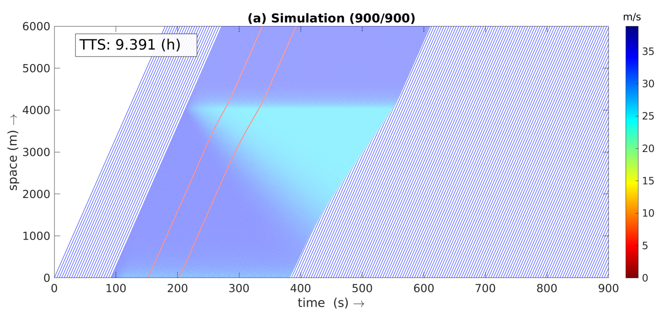


(g)



(h)



(i)

Figure C.1: Emergent patterns for friction coefficient 0.3 - 0.7 and tau 0.2

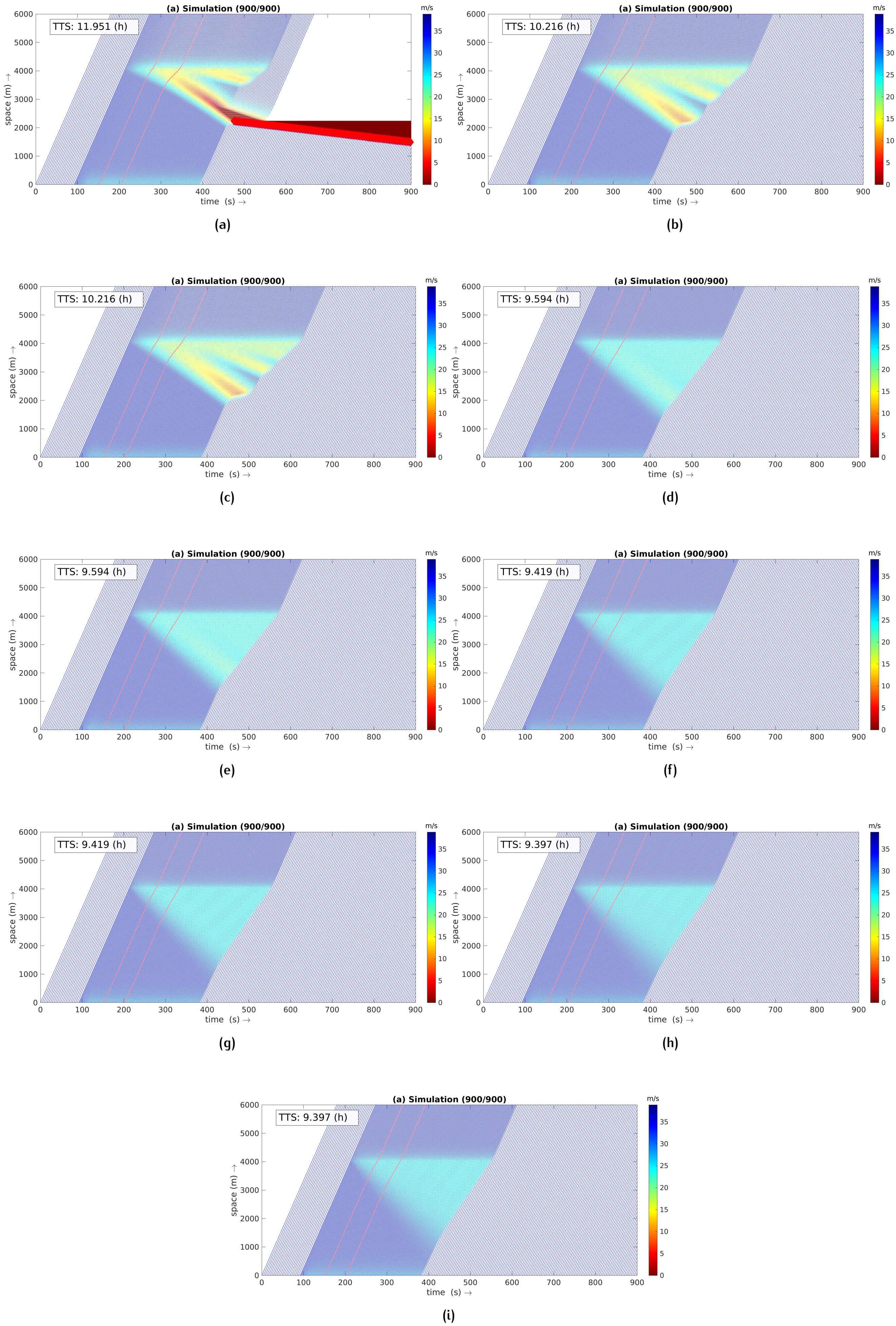
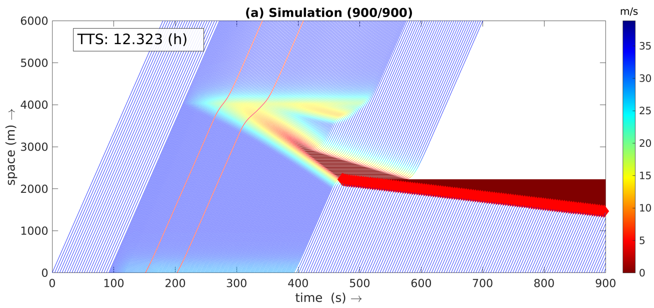
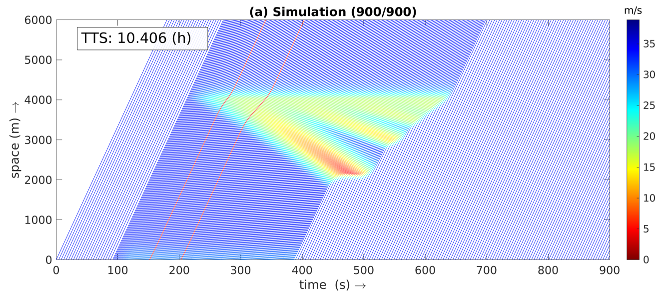


Figure C.2: Emergent patterns for friction coefficient 0.3 - 0.7 and tau 0.4



(a)



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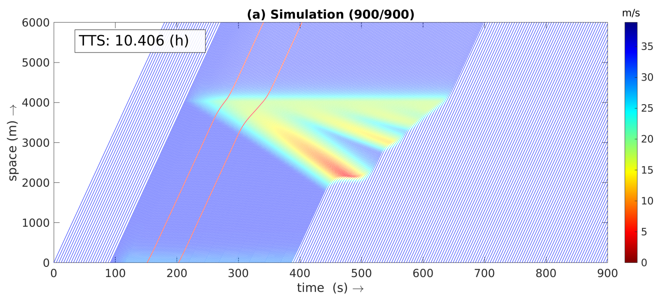
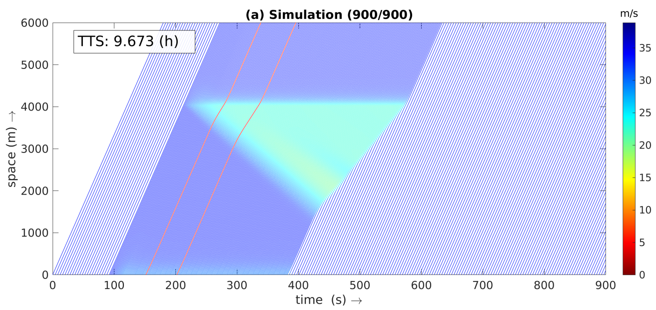
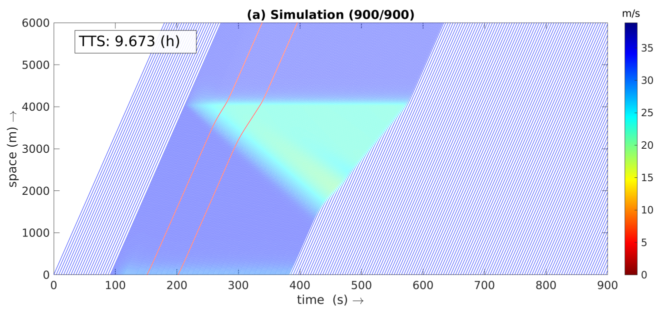


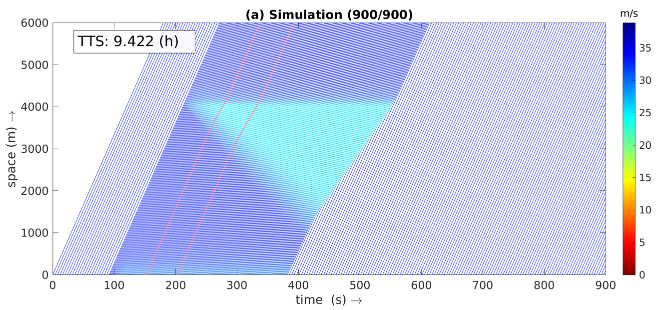
(c)



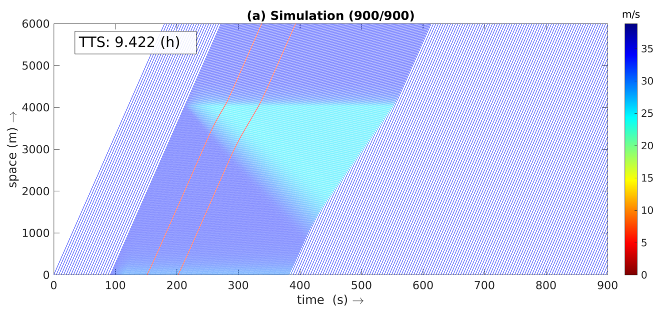
(d)



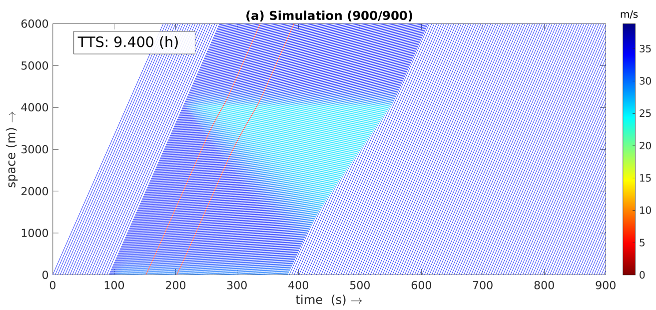
(e)



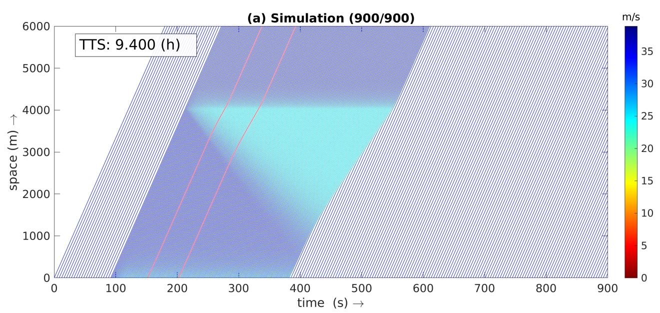
(f)



(g)

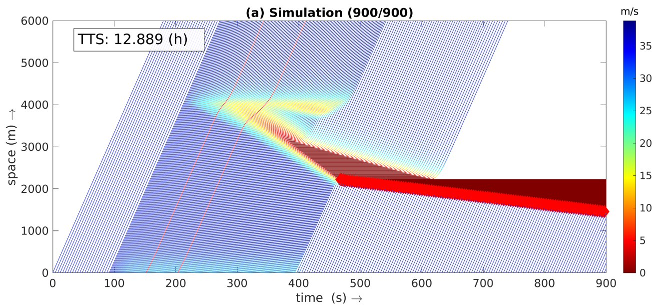


(h)

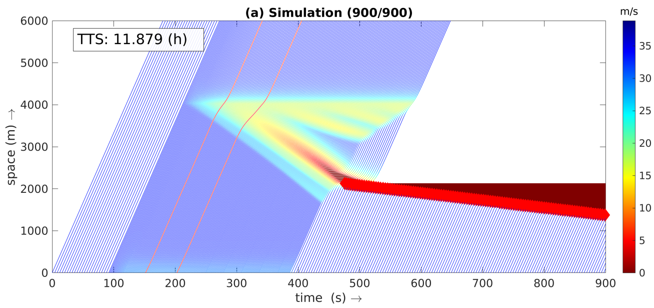


(i)

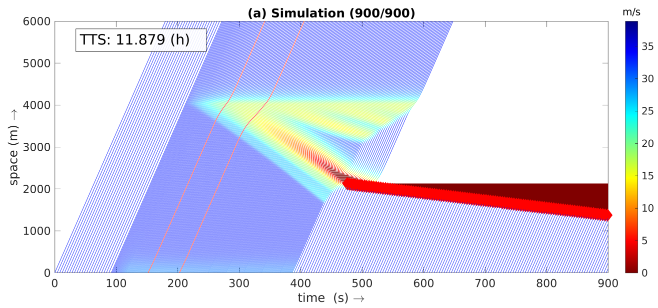
Figure C.3: Emergent patterns for friction coefficient 0.3 - 0.7 and tau 0.5



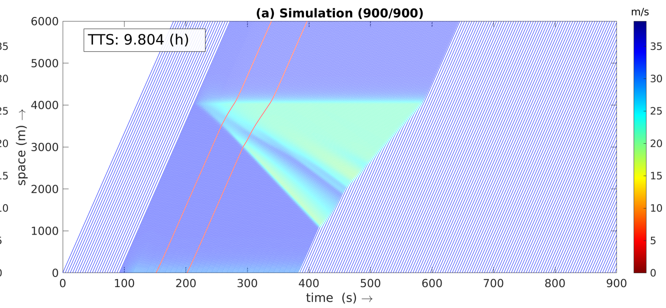
(a)



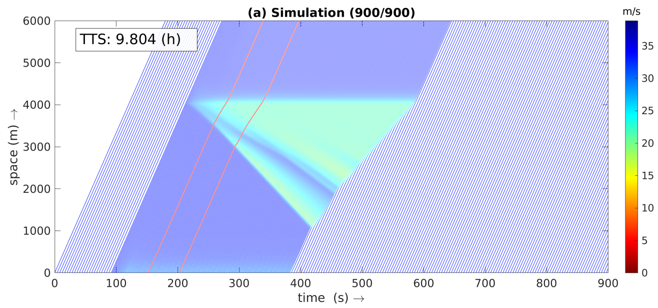
(b)



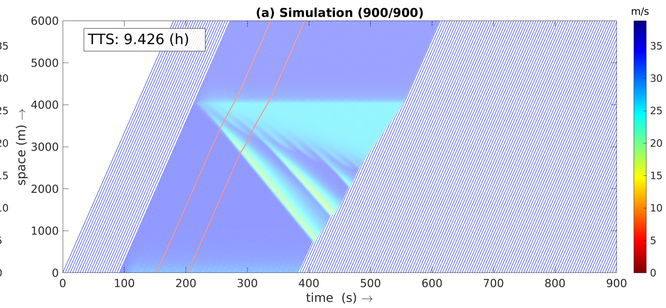
(c)



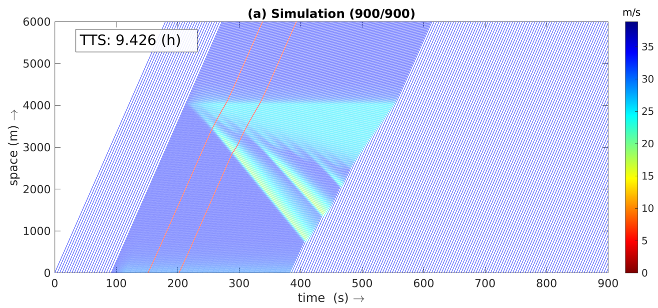
(d)



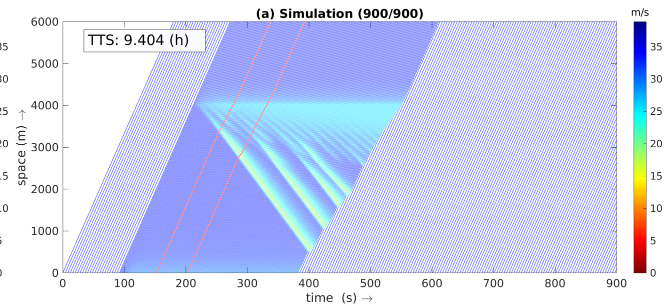
(e)



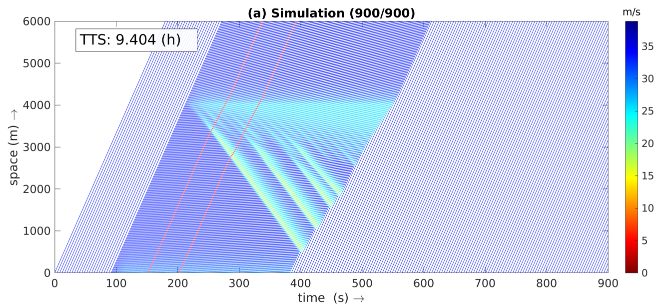
(f)



(g)



(h)



(i)

Figure C.4: Emergent patterns for friction coefficient 0.3 - 0.7 and tau 0.6

D NUMERICAL INTEGRATION

For the traffic flow applications and especially in the category for one lane simulation we prefer to exploit the ″balistic″ assumption to solve the following ordinary differential equation:

$$\frac{dv_n(t)}{dt} = a_{mic}(s_n, v_a, v_l) \tag{D.1}$$

rather than exploiting more advanced numerical integration techniques such as *Runge - Kutta* scheme. The ″balistic″ assumption postulates that the acceleration during each time step (Δt) remains the same and thus the numerical upgrade of the velocity and position of every vehicle can be calculated by the following equations:

$$\frac{dx_n(t+\Delta t)}{dt} = v_n(t) + \frac{dv_n(t)}{dt} * \Delta t \tag{D.2}$$

and

$$x_n(t+\Delta t) = x_n(t) + \left(\frac{dv_n(t)}{dt} + \frac{dv_n(t+\Delta t)}{dt}\right) * \Delta t/2 \tag{D.3}$$

TU Delft